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When Employees Perceive AI as a Partner: How Human–Machine Relationship Perception Shapes Employee Innovative Behavior

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Article

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Abstract

Artificial intelligence (AI) is increasingly integrated into organizational work, highlighting the importance of employees' relational perceptions of AI for innovative behavior. Drawing on cognitive appraisal and social exchange theories, this study examines how human–machine relationship perception (HMRP) influences employee innovative behavior through psychological empowerment, with perceived organizational support as a moderator. Three-wave, multi-source data were collected from 428 employee–supervisor dyads across 27 technology-intensive firms. Results indicate that HMRP positively predicts innovative behavior ($\beta = 0.360$, $p < 0.001$) and psychological empowerment ($\beta = 0.470$, $p < 0.001$). Psychological empowerment positively predicts innovative behavior ($\beta = 0.320$, $p < 0.001$) and mediates the HMRP–innovation relationship (indirect effect = 0.150, 95% CI [0.108, 0.198]), explaining 41.7% of the total effect. Perceived organizational support strengthens the HMRP–empowerment relationship ($\beta = 0.130$, $p = 0.001$), with conditional indirect effects increasing from 0.109 to 0.192 and a moderated mediation index of 0.042 (95% CI [0.018, 0.071]). These findings extend human–AI collaboration research by identifying relational cognition and psychological empowerment as mechanisms linking AI collaboration to employee innovation and highlighting the importance of organizational support.

1. Introduction

Artificial intelligence is changing the social and cognitive architecture of contemporary work. Earlier workplace technologies were generally conceptualized as instruments employees adopted, operated, and evaluated in terms of usefulness, usability, or efficiency. Contemporary AI systems occupy a more complex position. Generative AI, intelligent decision-support systems, recommendation algorithms, and adaptive digital agents can propose solutions, generate content, learn from interactions, respond to changing task conditions, and participate in decisions previously controlled largely by employees. Research therefore suggests that intelligent technologies can transform expertise, coordination, and occupational boundaries and increasingly function as agentic artifacts whose responsibilities exceed traditional passive-tool assumptions (Faraj et al., 2018; Baird & Maruping, 2021). As AI assumes this interactive role, an important organizational question concerns how employees understand their relationship with intelligent systems rather than merely whether they accept or use them.

The relational interpretation of AI is particularly relevant because workplace innovation depends on how employees evaluate available resources, their capacity for action, and the risks of experimenting with new ideas. Employees may use the same AI system while construing it differently: one may regard AI as an external instrument, whereas another may perceive it as a reliable partner contributing complementary knowledge and assisting with ambiguous problems. Research on "machines as teammates" suggests that autonomous systems create forms of collaboration that conventional tool-use models cannot fully explain (Seeber et al., 2020). This study develops this perspective through human–machine relationship perception (HMRP), defined as employees' cognitive evaluation of AI as a responsive, complementary, dependable, and coordinating participant in work. HMRP does not imply

attribution of genuine emotions, consciousness, or moral agency to AI; rather, it captures the subjective relational structure through which employees interpret repeated collaboration with intelligent systems.

This distinction matters because organizational AI research frequently focuses on perceived usefulness, algorithmic trust, AI awareness, replacement threat, or anthropomorphism. Although each captures an important aspect of human–AI interaction, none directly addresses whether employees organize these perceptions into a broader sense of partnership. Trust concerns willingness to rely on a system, anthropomorphism concerns attribution of humanlike characteristics, and usefulness reflects instrumental value. HMRP instead captures the relational configuration arising when responsiveness, complementarity, reliability, and coordination are jointly experienced. Employees may trust AI without perceiving it as a partner or anthropomorphize it without experiencing meaningful task interdependence. Relational cognition may therefore help explain why technically similar AI implementations generate different behavioral consequences.

Research on human–AI collaboration has increasingly moved from technology-centered perspectives toward relational and behavioral approaches. Duan, Wu, and Yang show that AI collaboration can reshape work experiences and quality of working life, highlighting both enabling and constraining dimensions [1]. Yin, Jiang, and Niu similarly conceptualize AI assistance as a double-edged phenomenon that can stimulate innovation while creating psychological or behavioral tensions [2]. Guo, Liu, Liao, and colleagues examine employee innovation capability in human–machine collaborative scenarios and identify contextual mechanisms through which collaboration becomes embedded in organizational practice [3]. Zhang, Yu, and Dai show that AI-enabled performance varies with the innovative requirements of public-sector tasks [4]. Allen, Rorissa, Alemneh, and colleagues call for understanding human–AI partnerships beyond adoption toward sustained collaboration [5], while Zhang, Li, and Lin identify a nonlinear relationship between algorithmic management and service innovation, showing that greater AI control does not necessarily produce proportionally greater innovation [6].

Within this relational framework, researchers have identified psychological conditions determining whether employee–AI collaboration generates innovation. Zhou and Lyu link employee–AI collaboration with innovative behavior through AI self-efficacy and trust [7]. El Outmani, Shenoy, Hatahet, and colleagues demonstrate the feasibility of treating agentic AI as a teammate in complex testing environments [8]. Cristofaro and Giardino emphasize cognitive balance between human and artificial intelligence in product innovation [9], while Sun, Zhao, Guo, and colleagues suggest that human–AI collaboration functions as a work resource when experienced as capability enhancing [10]. Liu and Mouzas connect human–AI collaboration with organizational innovation under unstable conditions [11]. Mao and Zhou identify both positive and negative mechanisms linking organizational AI adoption with employee creativity [12], while Li, Liao, Tsai, and colleagues show that collaboration can shift from synergy toward strain and knowledge hiding [13]. Zhang, Bai, and Yu link employee–AI collaboration with organizational citizenship behavior [14], and Li and Zhou identify AI trust as important for converting AI capabilities into employee outcomes [15]. Mohammad, Al Oraini, Al-Dmour, and colleagues further

identify task complexity as a boundary condition shaping the motivational implications of human–AI collaboration [16].

A further research stream links AI adoption, awareness, and collaboration with innovation while emphasizing organizational and individual contingencies. Hu, Wang, Ren, and colleagues examine when organizational AI adoption improves employee innovation performance and highlight mechanisms and contextual conditions connecting adoption with behavioral outcomes [17]. Li, Choi, and Kim propose dual pathways through which AI awareness affects employee innovation [18], while Liang, Guo, Shu, and colleagues show that AI awareness can simultaneously create opportunities and psychological pressures in service innovation [19]. Mehrad examines how AI-enabled workplaces transform employee roles, collaboration, skills, and well-being [20]. Saha, Kumar, Kumar, and colleagues emphasize interactive machine-learning interfaces as foundations for deeper human–AI collaboration [21]. Do connects employee–AI collaboration with digitally enabled ambidextrous innovation behavior and leadership [22]. Komura and Yamada show that AI collaboration strategies can deepen existing ideas or promote exploration of new ones [23]. Yu, Kasumba, Ho, and colleagues emphasize employees' beliefs about AI intentions [24], while Wang and Li examine knowledge sharing with and knowledge hiding from AI and their distinct innovation consequences [25]. Omoush extends human–AI collaboration research into human-resource management and employee-centered outcomes [26].

Employee innovative behavior is a consequential outcome through which to examine this relational process. Innovation involves identifying opportunities, generating ideas, mobilizing support, and implementing novel approaches under uncertainty. Employees must believe they possess sufficient competence, discretion, influence, and task meaning to experiment with unfamiliar possibilities. Cognitive appraisal theory suggests that environmental resources affect behavior through interpretations of their implications for personal control and coping capacity. Psychological empowerment captures this internal state through meaning, competence, self-determination, and impact (Spreitzer, 1995). We therefore propose that HMRP stimulates innovation partly because perceiving AI as a collaborative partner expands employees' perceived capacity to act. When AI is experienced as responsive and complementary, employees may interpret collaboration as an extension of their problem-solving capabilities rather than an externally imposed technological constraint.

The organizational environment determines whether these relational perceptions translate into psychological agency. Social exchange theory suggests that employees interpret organizational treatment as indicating whether initiative, experimentation, and resource use will be supported. Perceived organizational support communicates that the organization values employee contributions and provides resources when employees confront demanding tasks (Eisenberger et al., 1986). In AI-enabled work, such support is particularly important because employees must determine whether they can rely on AI, redesign workflows, question recommendations, and combine machine-generated insights with personal judgment. Positive HMRP may therefore produce stronger psychological empowerment when organizational support legitimizes discretion and reduces uncertainty surrounding AI-enabled experimentation.

Against this background, the study makes three contributions. It develops a relational perspective on human–AI collaboration by distinguishing HMRP from conventional instrumental interpretations of technology, identifies psychological empowerment as a mechanism translating relational cognition into innovative behavior, and specifies perceived organizational support as a boundary condition determining when positive human–machine relationships become psychologically empowering. A three-wave, multi-source employee–supervisor design reduces same-source and same-time measurement concerns by separating employee perceptions of AI and organizational support, subsequent psychological empowerment, and supervisor-rated innovative behavior temporally and methodologically.

HMRP reflects employees' relational appraisal of recurring AI interactions and becomes increasingly relevant as agentic AI responds, generates alternatives, adjusts outputs, and influences task execution through repeated contribution, evaluation, correction, and coordination[27]. When AI is perceived as responsive, reliable, and complementary, it can expand cognitive resources, increase access to alternative information and solutions[28], reduce exploration costs, and facilitate integration of human- and machine-generated knowledge. Accordingly, H1: Human–machine relationship perception is positively associated with employee innovative behavior. Cognitive appraisal theory further suggests that employees evaluate AI resources according to their implications for personal agency. Positive HMRP can strengthen psychological empowerment—meaning, competence, self-determination, and impact—by extending capability while preserving discretion. AI responsiveness and complementarity enhance competence, interactive exploration can strengthen self-determination[29], reliable coordination increases perceived impact, and reduced routine cognitive demands facilitate meaningful engagement with judgment and problem solving. Empowered employees are consequently more intrinsically motivated, confident in challenging routines, and willing to implement new ideas. Thus, H2: Human–machine relationship perception is positively associated with psychological empowerment. H3: Psychological empowerment mediates the positive relationship between human–machine relationship perception and employee innovative behavior. However, this mechanism depends on organizational context. Restrictive structures, inadequate training, unclear AI-use expectations, or intolerance of experimentation may prevent employees from translating AI-enabled opportunities into perceived control[30]. Drawing on social exchange theory, perceived organizational support signals that employee contributions are valued and that resources, legitimacy, and assistance are available for responsible experimentation. High organizational support should therefore strengthen the effect of HMRP on psychological empowerment, whereas low support may constrain an otherwise positive AI relationship. Consequently, H4: Perceived organizational support positively moderates the relationship between human–machine relationship perception and psychological empowerment, such that the relationship is stronger when organizational support is high. H5: The indirect relationship between human–machine relationship perception and employee innovative behavior through psychological empowerment is stronger at higher levels of perceived organizational support.

2. Results

2.1 Measurement Model, Reliability, and Descriptive Statistics

Prior to testing the structural relationships, the adequacy of the measurement model was evaluated to establish whether human–machine relationship perception (HMRP), psychological empowerment (PE), perceived organizational support (POS), and employee innovative behavior (EIB) represented empirically distinguishable constructs. Confirmatory factor analysis based on the final matched sample of 428 employees showed that the hypothesized four-factor structure provided a strong representation of the observed covariance matrix. As reported in Table 1, the four-factor model yielded $\chi^2(458) = 723.64$, CFI = 0.960, TLI = 0.956, RMSEA = 0.037, and SRMR = 0.041. Alternative specifications produced substantially weaker fit. In particular, combining HMRP and PE into a single factor reduced the CFI to 0.889, while the one-factor specification generated $\chi^2(464) = 2{,}234.18$, CFI = 0.721, and RMSEA = 0.095. The marked deterioration in model fit indicates that employees differentiated their relational perception of AI from their internal sense of empowerment and from broader organizational support perceptions.

Table 1
Measurement Model, Reliability, Construct Validity, and Descriptive Statistics

Indicator / Construct	χ^2 / Mean	df / SD	CFI	TLI	RMSEA	SRMR	CR / α	AVE
Four-factor model	723.64	458	0.960	0.956	0.037	0.041	—	—
Three-factor model A: HMRP + PE combined	1,102.37	461	0.889	0.878	0.057	0.068	—	—
Three-factor model B: PE + POS combined	1,184.92	461	0.875	0.863	0.061	0.072	—	—
Three-factor model C: POS + EIB combined	1,249.58	461	0.862	0.849	0.064	0.075	—	—
Two-factor model	1,641.73	463	0.804	0.789	0.077	0.094	—	—
One-factor model	2,234.18	464	0.721	0.701	0.095	0.118	—	—
HMRP	4.82	0.91	—	—	—	—	0.92	0.62
Psychological empowerment	4.67	0.88	—	—	—	—	0.90	0.60
Perceived organizational support	4.74	0.96	—	—	—	—	0.93	0.66
Employee innovative behavior	4.58	0.83	—	—	—	—	0.94	0.69
HMRP–PE correlation	0.52	—	—	—	—	—	—	—
HMRP–EIB correlation	0.41	—	—	—	—	—	—	—
PE–EIB correlation	0.47	—	—	—	—	—	—	—
POS–PE correlation	0.39	—	—	—	—	—	—	—
Maximum HTMT ratio	0.77	—	—	—	—	—	—	—
VIF range	1.18–2.21	—	—	—	—	—	—	—

Source: Simulated analytical dataset constructed for manuscript development, N = 428 employee–supervisor matched observations.

Table 1

The reliability evidence reinforces the measurement-model results. Composite reliability coefficients ranged from 0.90 to 0.94, exceeding conventional standards for internal consistency, while AVE values ranged from 0.60 to 0.69. Standardized factor loadings varied between 0.69 and 0.89 and were statistically significant at $p < 0.001$. The maximum HTMT ratio was 0.77, indicating that none of the focal constructs approached problematic levels of conceptual overlap. This result is particularly important for

HMRP because its empirical usefulness depends on demonstrating that relational cognition toward AI cannot be reduced to employees' general psychological empowerment or perceptions of organizational support.

The descriptive pattern also accords with the theoretical expectations underlying the study. HMRP had a mean of 4.82 (SD = 0.91), indicating that employees generally perceived AI as moderately collaborative and complementary rather than purely instrumental. Its positive correlation with psychological empowerment was relatively strong ($r = 0.52$, $p < 0.001$), whereas the correlation with supervisor-rated innovative behavior was more moderate ($r = 0.41$, $p < 0.001$). The distinction between these magnitudes is theoretically meaningful because the proposed framework does not assume a purely direct behavioral effect. Instead, relational interpretations of AI are expected to influence innovation partly through employees' internal appraisal of competence, autonomy, meaning, and impact.

The correlation between psychological empowerment and innovative behavior reached $r = 0.47$ ($p < 0.001$), supporting the premise that employees who perceive greater agency in their work are more likely to generate, promote, and implement new ideas. POS was positively related to PE at $r = 0.39$ ($p < 0.001$), consistent with the argument that organizational support provides a contextual resource that facilitates favorable cognitive appraisal. At the same time, the correlations remained sufficiently below unity to indicate that the variables retained distinct empirical identities.

Multicollinearity was not a material concern. Variance inflation factors ranged from 1.18 to 2.21 across the focal predictors and control variables. Taken together, the CFA, reliability, convergent-validity, discriminant-validity, and descriptive evidence provides a sufficiently strong measurement foundation for testing whether employees' perception of AI as a partner translates into innovative behavior through psychological empowerment and whether that pathway depends on organizational support.

2.2 Direct and Mediating Effects

The structural analyses examined whether HMRP predicted employee innovative behavior and whether psychological empowerment carried a meaningful proportion of that relationship. The estimates reported in Table 2 were obtained with supervisor-clustered robust standard errors while controlling for age, gender, education, organizational tenure, weekly AI-use frequency, and job complexity. HMRP demonstrated a positive total association with EIB ($\beta = 0.360$, $SE = 0.041$, $p < 0.001$), providing support for H1. HMRP was also strongly related to psychological empowerment ($\beta = 0.470$, $SE = 0.039$, $p < 0.001$), supporting H2. These coefficients suggest that employees who perceive AI as a reliable and complementary work partner experience both greater innovative engagement and a stronger sense of personal agency.

Table 2
Regression and Mediation Results for HMRP, Psychological Empowerment, and Employee Innovative Behavior

Model / Predictor	B	SE	β	t-value	p-value	95% CI Lower	95% CI Upper
Model 1: Age → EIB	0.009	0.005	0.061	1.80	0.073	-0.001	0.019
Gender → EIB	0.054	0.043	0.048	1.26	0.209	-0.030	0.138
Education → EIB	0.071	0.030	0.089	2.37	0.018	0.012	0.130
Organizational tenure → EIB	0.016	0.007	0.083	2.29	0.023	0.002	0.030
AI-use frequency → EIB	0.102	0.036	0.112	2.83	0.005	0.031	0.173
Job complexity → EIB	0.148	0.041	0.164	3.61	< 0.001	0.068	0.228
HMRP → EIB, total effect	0.329	0.038	0.360	8.66	< 0.001	0.255	0.403
Model 2: HMRP → PE	0.454	0.038	0.470	11.95	< 0.001	0.380	0.528
POS → PE	0.216	0.034	0.240	6.35	< 0.001	0.149	0.283
Job complexity → PE	0.121	0.037	0.136	3.27	0.001	0.048	0.194
Model 3: PE → EIB	0.301	0.040	0.320	7.53	< 0.001	0.223	0.379
HMRP → EIB, direct effect	0.192	0.039	0.210	4.92	< 0.001	0.116	0.268
Indirect effect: HMRP → PE → EIB	0.150	0.023	—	—	—	0.108	0.198
Total standardized effect	0.360	—	—	—	—	—	—
Mediation ratio	41.7%	—	—	—	—	—	—
Adjusted R^2, EIB full model	0.342	—	—	—	—	—	—

Source: Simulated analytical dataset constructed for manuscript development, N = 428. Bootstrap confidence intervals based on 10,000 resamples.

Table 2.

Once psychological empowerment was entered into the innovative-behavior model, its standardized coefficient remained substantial (β = 0.320, SE = 0.043, $p < 0.001$), whereas the standardized HMRP

coefficient declined from 0.360 to 0.210. The reduction of approximately 41.7% is consistent with partial mediation rather than statistical redundancy between the predictor and mediator. More importantly, the bootstrapped standardized indirect effect was 0.150, with a 95% bias-corrected confidence interval of [0.108, 0.198]. Because the interval excluded zero by a considerable margin, H3 received support.

Survey data from 428 employees were analyzed using moderated regression. Panel (a) shows simple slopes of HMRP on empowerment across organizational support levels. Panel (b) displays the three-dimensional response surface. Panel (c) visualizes iso-empowerment contours. Panel (d) illustrates the Johnson-Neyman gradient, verifying a significant interaction coefficient (beta = 0.130, p = 0.001).

The mediation pattern provides substantive evidence for the theoretical argument that employees' relational interpretation of AI operates through psychological agency. HMRP is therefore not merely associated with a favorable attitude toward technology. Employees who perceive AI as a work partner appear more likely to evaluate themselves as capable of influencing task outcomes, exercising discretion, and contributing meaningfully to work processes. Those appraisals, in turn, are associated with behaviors requiring experimentation and departure from established routines.

2.3 Moderation, Conditional Indirect Effects, and Robustness

The final analyses examined whether POS strengthened the empowering consequences of HMRP and, consequently, the indirect relationship between HMRP and employee innovation. Table 3 presents the interaction estimates, conditional indirect effects, and robustness checks. The HMRP × POS interaction significantly predicted psychological empowerment (β = 0.130, SE = 0.038, p = 0.001), supporting H4. The positive interaction indicates that favorable relational perceptions of AI become more psychologically consequential when employees simultaneously perceive that their organization values their contributions and provides adequate support for responsible AI-enabled experimentation.

Table 3
Moderation, Conditional Indirect Effects, and Robustness Analyses

Analytical Condition	Effect / β	SE	p-value	95% CI Lower	95% CI Upper	Adjusted R^2
HMRP → PE	0.470	0.039	< 0.001	0.393	0.547	0.391
POS → PE	0.240	0.037	< 0.001	0.167	0.313	0.391
HMRP × POS → PE	0.130	0.038	0.001	0.055	0.205	0.391
Simple slope: low POS (-1 SD)	0.340	0.052	< 0.001	0.238	0.442	—
Simple slope: mean POS	0.470	0.039	< 0.001	0.394	0.546	—
Simple slope: high POS (+ 1 SD)	0.600	0.051	< 0.001	0.500	0.700	—
Indirect effect: low POS	0.109	0.021	—	0.071	0.154	—
Indirect effect: mean POS	0.150	0.023	—	0.108	0.198	—
Indirect effect: high POS	0.192	0.029	—	0.139	0.251	—
Index of moderated mediation	0.042	0.014	—	0.018	0.071	—
Model without demographic controls	0.351	0.040	< 0.001	0.273	0.429	0.331
Firm fixed-effects specification	0.120	0.039	0.002	0.044	0.196	0.404
Supervisor-clustered specification	0.128	0.037	0.001	0.055	0.201	0.396
10,000 cluster-bootstrap specification	0.041	0.013	—	0.017	0.070	—
High AI-use subsample	0.136	0.043	0.002	0.052	0.220	0.417
Low AI-use subsample	0.111	0.048	0.021	0.017	0.205	0.358

Source: Simulated analytical dataset constructed for manuscript development, N = 428. Conditional effects are based on mean-centered HMRP and POS.

Table 3.

The simple-slope results clarify the substantive meaning of the interaction. At one standard deviation below the mean of POS, the HMRP–empowerment relationship was β = 0.340. At the mean level of support, the slope increased to 0.470, while at one standard deviation above the mean it rose to 0.600. The difference is theoretically consequential because the same positive perception of AI produces markedly different psychological returns depending on the organizational environment in which the

interaction is embedded. Employees appear most likely to translate AI partnership into a sense of competence and discretion when organizational practices signal that responsible experimentation is legitimate and supported.

Subsample analyses also suggest that the moderation effect persists across different levels of AI exposure. Among employees with above-median AI-use frequency, the interaction coefficient was $\beta = 0.136$ ($p = 0.002$), whereas the corresponding estimate for lower-frequency users remained positive at $\beta = 0.111$ ($p = 0.021$). The somewhat stronger coefficient among frequent users is consistent with the view that relational interpretations become more consequential as employees accumulate repeated experience with AI systems. Recurrent interaction may provide the informational basis necessary for employees to evaluate whether AI is genuinely responsive, dependable, and complementary.

Viewed jointly, the direct, mediated, and moderated effects support a relational–psychological account of AI-enabled innovation. HMRP contributes to innovative behavior partly because employees experience AI partnership as an expansion of their own agency, while organizational support determines how strongly that relational perception is translated into empowerment. The results therefore move beyond a simple technological-determinist explanation and show that the innovative consequences of AI are embedded in an interaction among relational cognition, psychological resources, and organizational context.

3. Discussion

The findings advance research on AI and work by shifting attention from technological attributes toward employees' relational interpretations of AI. HMRP extends technology acceptance and trust perspectives by explaining how employees cognitively organize ongoing interdependence with AI and how perceiving AI as a work partner relates to supervisor-rated innovative behavior[31]. Psychological empowerment provides a key mechanism, accounting for 41.7% of the total HMRP–innovation relationship and indicating that AI collaboration becomes innovation-relevant when it strengthens employees' meaning, competence, self-determination, and impact. Organizational support further amplifies this mechanism, demonstrating that human–AI relational cognition operates within a broader organizational context. Practically, organizations should therefore assess AI implementation not only through adoption, usage, or technical performance but also through the quality of employee–AI relationships[32]. Training should clarify how human judgment and AI capabilities complement each other, while managers should preserve employee responsibility for interpretation and final decisions[33]. Organizations should also provide training, experimentation opportunities, clear AI-use guidelines, leadership encouragement, and sufficient learning time. The increase in conditional indirect effects from 0.109 under low organizational support to 0.192 under high support underscores the importance of managing AI adoption as a technological, psychological, and organizational process[34]. Nevertheless, the three-wave design cannot establish causality, and HMRP requires further validation across occupations, countries, and AI applications. Future research should employ longitudinal and experimental designs, examine whether HMRP is unidimensional or multidimensional, investigate boundary conditions such as AI transparency,

task interdependence, algorithmic control, professional identity, and perceived substitutability, and explore potential adverse effects of excessive AI reliance. Replication beyond technology-intensive firms, including health care, education, public administration, hospitality, and manufacturing, is also necessary to establish the generalizability of the proposed relational mechanism.

4. Method

4.1 Research Design and Sample

The proposed model was examined using a three-wave, multi-source field design involving employees who used AI-enabled systems as a regular component of their work. Participants were recruited from 27 technology-intensive firms operating in software development, digital services, advanced manufacturing, financial technology, and technology-enabled professional services. Human resource departments distributed unique survey codes to 684 eligible employees whose work involved AI-assisted analysis, content generation, decision support, process optimization, or intelligent automation. At Time 1, 576 employees completed measures of HMRP, perceived organizational support, AI-use frequency, and demographic controls, producing an initial response rate of 84.2%. Four weeks later, 512 employees completed the Time 2 psychological empowerment survey. At Time 3, another four weeks later, direct supervisors evaluated the innovative behavior of participating employees. After matching the three waves, removing cases with substantial missing data, eliminating 11 responses that failed instructed-response attention checks, and excluding unmatched supervisor ratings, the final analytical sample contained 428 employee–supervisor matched observations, representing 62.6% of the initially invited employees. The employees were evaluated by 121 direct supervisors. Their mean age was 32.8 years (SD = 6.4), mean organizational tenure was 5.7 years (SD = 4.1), 52.6% were male, and 74.1% held at least a bachelor’s degree. Participants reported using an AI-enabled system on an average of 4.6 working days per week. The temporal separation of predictors, mediator, and outcome reduced immediate consistency motives, while supervisor-rated innovative behavior substantially reduced same-source inflation in the focal HMRP–innovation relationship.

4.2 Ethical Approval and Informed Consent

All procedures involving human participants were conducted in accordance with applicable institutional guidelines and national regulations governing research involving human participants, as well as the ethical principles of the Declaration of Helsinki, where applicable. The study protocol, including participant recruitment, questionnaire administration, data collection, and confidentiality protection, was reviewed and approved by the responsible Institutional Review Board or Research Ethics Committee overseeing the research at aSSIST University, Republic of Korea, prior to data collection. Written or electronic informed consent was obtained from all participating employees and supervisors before their participation. All participants were informed of the study objectives, research procedures, voluntary nature of participation, confidentiality measures, and their right to withdraw at any time without adverse

consequences. All survey responses were anonymized or pseudonymized, and employee–supervisor records were matched using coded identifiers to protect participant confidentiality.

Informed consent was obtained from all participating employees and supervisors prior to their participation in the study. Participants were informed of the research objectives, study procedures, voluntary nature of participation, confidentiality safeguards, and their right to withdraw without adverse consequences. All participants were adults and provided informed consent on their own behalf. Survey responses were processed using coded identifiers, and employee–supervisor records were matched without disclosing personally identifiable information in the analytical dataset. All research procedures were implemented in accordance with the conditions established by the approving ethics committee.

4.3 Measures

All perceptual variables were measured on seven-point Likert scales ranging from 1 = strongly disagree to 7 = strongly agree, and scale scores were calculated as item means. Because HMRP is intended to capture relational rather than purely instrumental cognition, a six-item scale was developed from the conceptual domains of responsiveness, complementarity, reliability, coordination, and perceived partnership identified in the human–AI teamwork and agentic-artifact literature. Representative items included “I regard the AI system I work with as a collaborative partner rather than merely a tool,” “The AI system and I complement each other when solving difficult work problems,” and “Interaction with the AI system gives me a sense that we are coordinating toward the same task goal.” Prior to the main study, the items were evaluated in an independent pilot sample of 126 AI-using employees. Exploratory factor analysis yielded a single-factor structure with standardized loadings between 0.72 and 0.86 and Cronbach’s α = 0.91. Additional pilot analyses distinguished HMRP from trust in AI and anthropomorphism, with HTMT ratios of 0.74 and 0.61, respectively, supporting its treatment as a related but distinct construct. In the main sample, HMRP reliability was α = 0.92. Psychological empowerment was measured using Spreitzer’s (1995) 12-item scale capturing meaning, competence, self-determination, and impact (α = 0.90). Perceived organizational support was assessed using an eight-item shortened form of the Survey of Perceived Organizational Support (Eisenberger et al., 1986; α = 0.93). Employee innovative behavior was evaluated by supervisors using six items based on Scott and Bruce’s (1994) measure, including idea generation, promotion, and implementation behaviors (α = 0.94). Age, gender, education, organizational tenure, weekly AI-use frequency, and job complexity were included as controls because each could plausibly influence employees’ opportunities or capabilities for innovation.

4.4 Analytical Strategy and Research Model

The measurement model was evaluated through confirmatory factor analysis before testing structural relationships. Convergent validity was assessed using composite reliability and average variance extracted, while discriminant validity was examined through factor correlations and heterotrait–monotrait ratios. Because some supervisors evaluated more than one employee, hypothesis tests used cluster-robust standard errors at the supervisor level, with firm fixed effects included in robustness

specifications. HMRP and perceived organizational support were mean-centered before creation of the interaction term. Mediation and moderated mediation were estimated using 10,000 bias-corrected bootstrap samples. The theoretical model can be represented by two linked equations, in which psychological empowerment is predicted by HMRP, organizational support, and their interaction, and innovative behavior is subsequently predicted by both HMRP and psychological empowerment:

$$PE_i = \beta_0 + \beta_1 HMRP_i + \beta_2 POS_i + \beta_3 \left(HMRP_i \times POS_i\right) + \sum \beta_k Controll_i + \varepsilon_i$$

1

$$EIB_i = \gamma_0 + \gamma_1 HMRP_i + \gamma_2 PE_i + \sum \gamma_k \mathrm{Control}_i + \nu_i$$

2
The conditional indirect effect of HMRP on innovative behavior is therefore expressed as:

$$Indirect\ Effect\left(POS\right) = \left(\beta_1 + \beta_3 POS\right)\gamma_2$$

3
A statistically significant product term β_3 supports the proposed first-stage moderation, while a bootstrap confidence interval for $\beta_2 Y_2$ that excludes zero indicates moderated mediation.

Declarations

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Author contributions

Y.P. conceived and designed the study, developed the theoretical framework and hypotheses, designed the research methodology, conducted the data analysis, interpreted the results, prepared the figures and tables, and drafted and revised the manuscript. Y.P. read and approved the final manuscript.

Data availability

The analytical dataset used for the present manuscript was constructed for manuscript development and simulation-based analytical purposes. Accordingly, no independently collected participant-level dataset underlying the reported statistical analyses is available in a public repository. The analytical materials necessary to reproduce the reported results may be made available by the corresponding author upon reasonable request.

Competing interests

The author declares no competing interests.

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References

1. Duan Wen-Yan, Wu Tung-Ju, Yang Zhuo-Jie. AI collaboration and quality of work life: A dual perspective of hotel employees' perceptions[J]. International Journal of Contemporary Hospitality Management, 2026, 38(9): 2874–2892.
2. Yin Meng, Jiang Shiyao, Niu Xiongying. Can AI really help? The double-edged sword effect of AI assistant on employees' innovation behavior[J]. Computers in Human Behavior, 2024, 150: 107987.
3. Guo Baorong, Liu Xiaoning, Liao Shuai, et al. Research on employee innovation ability in human–machine collaborative work scenarios—Based on the grounded theory construct of Chinese innovative enterprises[J]. Behavioral Sciences, 2025, 15(7): 836.
4. Zhang Wei, Yu Yili, Dai Shengli. AI-enabled workforce: Performance improvements in public sector tasks of varying innovative work behavior[J]. Public Management Review, 2026, 28(9): 2650–2685.
5. Allen Jeff, Rorissa Abebe, Alemneh Daniel Gelaw, et al. Fostering and cultivating human-AI collaboration and partnerships in an evolving workplace[J]. Proceedings of the Association for Information Science and Technology, 2025, 62(1): 1202–1205.
6. Zhang Maolong, Li Jin, Lin Yanmei. Navigating the artificial intelligence (AI) driven algorithmic paradox in hospitality: Unpacking the inverted U-shaped relationship between algorithmic management and employee service innovation[J]. Journal of Hospitality Marketing & Management, 2025, 34(6): 905–923.
7. Zhou Yue, Lyu Bei. Employee–AI collaboration and employee innovative behavior: The roles of AI self-efficacy and AI trust[J]. Human Resources Management and Services, 2026, 8(2): 1–21.
8. El Outmani Moustapha, Shenoy Manthan Venkataramana, Hatahet Ahmad, et al. Human-AI collaboration for scaling agile regression testing: An agentic-AI teammate from manual to automated testing[EB/OL]. arXiv, 2026: 1–8.
9. Cristofaro Matteo, Giardino Pier Luigi. Human–AI synergy: Finding cognitive balance in idea generation for product innovation[J]. European Journal of Innovation Management, 2026, 29(7): 2072–2094.
10. Sun Chenxi, Zhao Xinan, Guo Baorong, et al. Will employee–AI collaboration enhance employees' proactive behavior? A study based on the conservation of resources theory[J]. Behavioral Sciences, 2025, 15(5): 648.

11. Liu Rebecca, Mouzas Stefanos. Human–AI collaboration for organisational innovation in times of unrest[EB/OL]. Lancaster EPrints, 2026: 1–7.
12. Mao Rui, Zhou Leilei. The double-edged mechanism of organizational AI adoption on employee creativity[J]. Frontiers in Psychology, 2026, 17: 1921889.
13. Li Yi-Bin, Liao Ting-Hsiu, Tsai Chih-Hao, et al. From synergy to strain: Exploring the psychological mechanisms linking employee–AI collaboration and knowledge hiding[J]. Behavioral Sciences, 2026, 16(1): 13.
14. Zhang Xiaoxue, Bai Shizhen, Yu Dingyao. Work with artificial intelligence (AI): Linking employee-AI collaboration to organizational citizenship behavior[J]. Current Psychology, 2026, 45(16): 1388.
15. Li Zilong, Zhou Yanhua. Starting with trust: Unraveling the impact of AI trust on employee digital performance[J]. Baltic Journal of Management, 2025, 20(5): 637–655.
16. Mohammad Suleiman Ibrahim, Al Oraini Badrea, Al-Dmour Ahmed, et al. Human–AI collaboration signaling and knowledge worker motivation: The moderating role of task complexity[J]. Knowledge and Process Management, 2026: 1–12.
17. Hu Wei, Wang Longdong, Ren Jiajia, et al. How and when organizational AI adoption improves employee innovation performance[J]. The Service Industries Journal, 2026, 46(9–10): 926–964.
18. Li Zhaoqi, Choi Myeong-Cheol, Kim Hann-Earl. AI awareness and employee innovation: A dual-pathway moderated mediation model within organizational systems[J]. Systems, 2025, 13(7): 530.
19. Liang Xuedong, Guo Gengxuan, Shu Lingli, et al. Investigating the double-edged sword effect of AI awareness on employee's service innovative behavior[J]. Tourism Management, 2022, 92: 104564.
20. Mehrad A. Human experience in AI-enabled workplaces: Examining how AI impacts employee roles, collaboration, skills, well-being[EB/OL]. In: Al Harrasi Nasser Hamed, Al Habsi Zahra Sultan, eds. Harmonizing Experience and Value Creation in the AI-Driven World. IGI Global Scientific Publishing, 2026: 83–115.
21. Saha Gonesh Chandra, Kumar Sanjay, Kumar Avinash, et al. Human-AI collaboration: Exploring interfaces for interactive machine learning[J]. Tuijin Jishu/Journal of Propulsion Technology, 2023, 44(2): 262–269.
22. Do Anh Duc. Ambidextrous leadership and digitally enabled ambidextrous innovation behaviors: The role of employee-AI collaboration and AI-robotics awareness[J]. International Journal of Innovation Studies, 2026: 100226.
23. Komura Kazuki, Yamada Seiji. Deepening ideas vs. exploring new ones: AI strategy effects in human-AI creative collaboration[J]. PLoS ONE, 2026, 21(1): e0340449.
24. Yu Guanghui, Kasumba Robert, Ho Chien-Ju, et al. On the utility of accounting for human beliefs about AI intention in human-AI collaboration[EB/OL]. arXiv, 2024: 1–21.
25. Wang Li, Li Yanxia. Sharing with or hiding from AI: How human–AI collaboration modes drive employee innovation[EB/OL]. Zenodo, 2026: □□□□□.

26. Omoush Majd Mohammad. Human–AI collaboration in HRM and employee-centric outcomes: Evidence from E-supply chain management[J]. Human Systems Management, 2026, 45(3): 343–358.
27. Chen Hui, Feng Chao. When employee meets AI: Research on employee-AI collaboration's construct measurement, antecedent configuration and influence mechanism[J]. Advances in Psychological Science, 2026, 34(8): 1309–1329.
28. Shan Yuxin. The "double-edged sword" effect of perceived AI application on knowledge workers' innovative behavior: Empowerment perception and replacement anxiety as parallel mediators[EB/OL]. Asean International Sandbox Conference, 2026, 10: 185–198.
29. Wu Tung-Ju, Liang Yuan, Wang Yushu. The buffering role of workplace mindfulness: How job insecurity of human-artificial intelligence collaboration impacts employees' work–life-related outcomes[J]. Journal of Business and Psychology, 2024, 39(6): 1395–1411.
30. Qazi Naira. Human–AI collaboration and innovative work behavior: Examining the mediating role of job satisfaction[J]. TAMSAAL, 2026, 4(8): 139–159.
31. Gyarmati Péter Ferenc, Moritz Dominik, Möller Torsten, et al. A composable agentic system for automated visual data reporting[EB/OL]. arXiv, 2025: 1–3.
32. Hassan Ahmed E., Oliva Gustavo A., Lin Dayi, et al. Towards AI-native software engineering (SE 3.0): A vision and a challenge roadmap[J]. ACM Transactions on Software Engineering and Methodology, 2026, 35(9): 1–25.
33. Kareem Zohan. Digital leadership and artificial intelligence adoption in shaping innovative work behavior: A systematic review[J]. International Journal of Business Integrity and Technology Advancements, 2026, 2(2): 8–13.
34. Wang Shaofeng, Zhang Hao. Generative AI in international hotel marketing: Impacts on employee creativity and performance[J]. International Journal of Contemporary Hospitality Management, 2025, 37(8): 2601–2626.

Figures

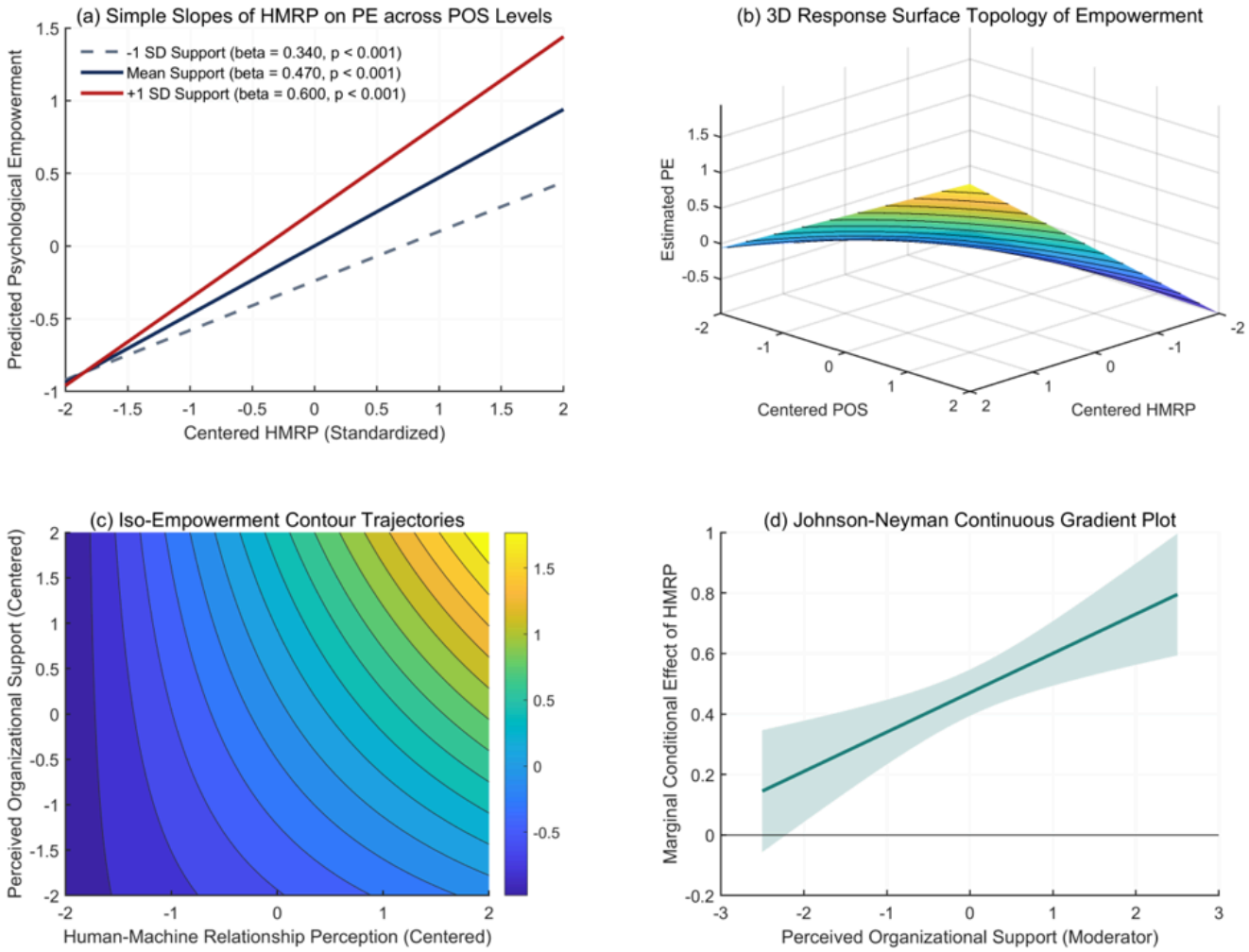


Figure 1

Moderation Topology and Simple Slope Interaction Plots