

THE AI WORKPLACE PARADOX: EXAMINING EMPLOYEE PERFORMANCE, AI-RELATED JOB ANXIETY, AND ORGANIZATIONAL COMMITMENT USING PLS-SEM

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ABSTRACT

Artificial intelligence (AI) is becoming embedded in everyday work, yet its employee-level consequences are inherently paradoxical. The same AI systems that expand information access, accelerate task completion, and support decision quality may also intensify concerns about skill obsolescence, role displacement, and the future value of human work. This study develops and tests an integrated model of the AI workplace paradox by examining the simultaneous effects of AI workplace integration on employee performance, AI-related job anxiety, and organizational commitment. Drawing on cognitive appraisal theory, conservation of resources theory, and the job demands-resources perspective, the model proposes that AI integration operates through two competing pathways: a resource-enabling pathway that enhances performance and a threat pathway that heightens job anxiety, thereby suppressing performance and commitment. Survey data were obtained from 428 employees working in AI-exposed knowledge-intensive organizations in India. Partial least squares structural equation modeling (PLS-SEM) with 5,000 bootstrap resamples was used to assess the measurement and structural models. The results show that AI workplace integration has a strong positive effect on employee performance ($\beta = 0.552$, $p < .001$) but also increases AI-related job anxiety ($\beta = 0.488$, $p < .001$). Job anxiety negatively affects performance ($\beta = -0.304$, $p < .001$) and organizational commitment ($\beta = -0.347$, $p < .001$), whereas performance strengthens commitment ($\beta = 0.397$, $p < .001$). Mediation analysis demonstrates competitive effects: the positive performance-mediated pathway is partly offset by anxiety-mediated pathways, leaving only a small total effect of AI integration on organizational commitment. The study contributes a process-based explanation of why technically successful AI implementation may coexist with psychologically fragile employee attachment. For managers, the findings imply that AI value realization requires simultaneous investment in task augmentation, reskilling, role clarity, procedural transparency, and employment-security communication.

Keywords: artificial intelligence; AI workplace integration; employee performance; AI-related job anxiety; organizational commitment; PLS-SEM; human-AI collaboration; technostress

1. INTRODUCTION

Artificial intelligence has moved from an experimental technology to an operational layer of contemporary organizations. Machine-learning systems, generative AI assistants, automated decision engines, intelligent analytics, algorithmic monitoring, and conversational agents increasingly participate in activities that were previously conducted exclusively by employees. This shift is especially visible in knowledge-intensive work, where AI can retrieve and synthesize information, generate text and code, support forecasting, automate routine cognitive steps, and offer recommendations at a speed that is difficult to match

through unaided human effort. Recent evidence accordingly links AI adoption with enhanced problem-solving efficacy, adaptive performance, and organizational process efficiency (Liu & Mei, 2026; Prasad & De, 2024). At the same time, a growing stream of research documents concerns regarding job replacement, skills obsolescence, loss of professional identity, algorithmic control, technostress, and resistance to AI-enabled work arrangements (Chen et al., 2025; Golgeci et al., 2025; Mirkhil, 2026).

These opposing outcomes create what this study terms the AI workplace paradox. At the employee level, AI may function simultaneously as a job resource and a job threat. As a resource, it can increase information availability, reduce repetitive workload, expand cognitive capacity, and support faster task execution. As a threat, it can signal that valued expertise is becoming replicable, that established work routines are unstable, and that future employment depends on continuous adaptation to opaque and rapidly changing systems. The paradox therefore cannot be understood adequately by asking only whether AI improves productivity or whether AI increases anxiety. A more consequential question is whether both processes occur at the same time and how their combined effects shape employees' willingness to remain psychologically attached to the organization.

Organizational commitment is particularly important in this context. Firms may introduce AI primarily to improve efficiency, service quality, responsiveness, and competitiveness, but implementation can be strategically self-defeating if employees interpret the same technology as evidence that their roles are temporary, their accumulated expertise is depreciating, or organizational decisions are becoming less human-centered. A technically efficient AI initiative may therefore increase measurable task performance while weakening the affective bond that sustains discretionary effort, cooperation, organizational citizenship, and retention. Research has begun to connect AI adoption and AI-related stress to commitment outcomes, but the mechanisms remain fragmented. For example, AI-enabled HR practices may enhance commitment when employees perceive competence and organizational support, whereas AI-related insecurity and psychologically threatening implementation can reduce attachment and well-being (Mo et al., 2025; Prasad & De, 2024).

A second gap concerns the dominant tendency to model AI-related outcomes as unidirectional. Studies often examine the beneficial pathway from AI use to performance or the adverse pathway from AI anxiety to strain. This separation is analytically convenient but theoretically incomplete. Automation-augmentation scholarship has long emphasized that technological systems can create contradictory consequences depending on how substitution and complementarity are experienced (Raisch & Krakowski, 2021). Recent workplace AI research similarly points to dual or competing effects. Liu and Mei (2026), for instance, show that AI adoption can improve adaptive performance through problem-solving efficacy, while AI anxiety research demonstrates that learning anxiety and replacement anxiety consume psychological resources and reduce positive work outcomes (Chen et al., 2025; Wang & Wang, 2022). What is still needed is an integrated empirical design that quantifies the enabling and anxiety pathways within the same structural model.

A third gap relates to methodological alignment. The AI-work literature is rapidly developing, with constructs and causal mechanisms still being refined. Partial least squares structural equation modeling (PLS-SEM) is well suited to such contexts because it supports prediction-oriented theory development, simultaneous assessment of direct and indirect effects, complex mediation structures, and latent-variable modeling under comparatively flexible distributional assumptions (Hair et al., 2022; Sarstedt et al., 2022). Although PLS-SEM has been used in studies of AI adoption, well-being, and performance, fewer studies

have used it specifically to estimate the net effect of competing employee-level AI pathways on organizational commitment.

The present study addresses these gaps by developing a four-construct model linking AI workplace integration, AI-related job anxiety, employee performance, and organizational commitment. It asks three research questions: (RQ1) Does AI workplace integration simultaneously improve employee performance and intensify job anxiety? (RQ2) How does AI-related job anxiety alter the relationship between AI integration and employee performance? and (RQ3) Do the performance-enhancing and anxiety-inducing pathways offset one another in predicting organizational commitment? The study is positioned in Indian knowledge-intensive organizations, a context characterized by rapid adoption of generative AI, intelligent automation, and algorithm-supported decision making across information technology/information technology-enabled services (IT/ITeS), banking and financial services, consulting, and other professional services.

The study contributes in four ways. First, it conceptualizes AI workplace integration as a dual-valence work condition rather than a uniformly beneficial or harmful technological exposure. Second, it connects cognitive appraisal theory and conservation of resources theory with the job demands-resources model to explain why the same technological change can be appraised as both an enabling resource and a threat to valued occupational resources. Third, it demonstrates competitive mediation: AI integration increases performance directly while also increasing anxiety, which suppresses performance and commitment. Fourth, it shows that the total relationship between AI integration and organizational commitment may be deceptively small because positive and negative indirect effects partly cancel one another. This distinction between weak total effects and strong underlying mechanisms is important for both research interpretation and managerial decision making.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 AI workplace integration as a dual-valence work condition

AI workplace integration refers to the extent to which AI-enabled systems are embedded in employees' routine work processes, decision activities, information search, task execution, and problem solving. The construct is broader than general attitudes toward AI and more behaviorally proximate than adoption intention. It reflects actual exposure to AI as part of the work architecture. In highly integrated environments, employees do not merely use an isolated application; they operate within workflows in which AI-generated outputs, automated recommendations, predictive scores, or generative systems influence how work is prioritized, executed, reviewed, and improved.

The performance case for such integration is compelling. AI can increase the speed of information processing, support pattern recognition, reduce repetitive cognitive effort, and allow employees to redirect attention toward judgment-intensive or relational aspects of work. Evidence from AI-adoption settings indicates that employees can use AI to improve problem-solving efficacy and adaptive performance (Liu & Mei, 2026). Research on generative AI in human resource and managerial contexts likewise shows associations with performance, engagement, and more effective organizational practices when employees trust and effectively use the technology (Prasad & De, 2024). From a job resources perspective, AI integration can therefore provide informational, cognitive, and operational resources that improve task accomplishment.

However, the same integration increases the salience of substitution. Employees observe AI performing tasks that previously demonstrated human expertise, and this can change how they assess the future value of their skills. Brougham and Haar's (2018) STARA framework

identifies employee awareness of smart technologies, AI, robotics, and algorithms as a source of concern about future careers. More recent AI-resistance research shows that fear, perceived inefficacy, mistrust, and existential questioning are central to employee resistance (Golgeci et al., 2025). AI integration is therefore not only a technical characteristic of work; it is also a psychological signal about the changing division of labor between humans and machines.

2.2 AI-related job anxiety

AI-related job anxiety is defined here as a work-focused state of apprehension concerning the implications of AI for role security, skill relevance, employability, and the employee's ability to keep pace with AI-enabled change. It draws on the job-replacement and learning-anxiety dimensions of the Artificial Intelligence Anxiety Scale developed by Wang and Wang (2022), while being explicitly contextualized to ongoing organizational AI integration. This focus distinguishes job anxiety from general discomfort with humanoid AI or broad societal concerns about AI.

Cognitive appraisal theory proposes that stress reactions depend on how individuals evaluate environmental demands relative to their goals and coping resources (Lazarus & Folkman, 1984). Workplace AI can be appraised as a challenge when it expands capability, but it can be appraised as a threat when employees anticipate displacement, reduced autonomy, intensified monitoring, or erosion of expertise. Conservation of resources (COR) theory complements this explanation by treating employment, professional status, skill value, competence, and social standing as resources that individuals seek to protect (Hobfoll, 1989). When AI is interpreted as threatening these resources, anxiety is a plausible psychological response.

Empirical research increasingly validates this concern. Wang and Wang (2022) established AI anxiety as a multidimensional construct involving learning and job replacement among other dimensions. Li and Huang (2020) similarly show that AI anxiety encompasses distinct fear-acquisition pathways. In work settings, Chen et al. (2025) report that job-replacement anxiety and learning anxiety reduce work passion through resource-depleting processes. Mirkhil (2026), using employees in India's banking, financial services, and insurance (BFSI) sector, finds AI anxiety to be a significant negative predictor of employee performance. These findings suggest that as AI becomes more deeply integrated into work, employee anxiety may rise even when the technology produces operational benefits.

2.3 Employee performance

Employee performance refers to behaviors and outcomes that contribute to organizational goals. Contemporary performance research distinguishes core task performance from contextual and adaptive contributions (Koopmans et al., 2013, 2014). This distinction is particularly relevant in AI-enabled work because technological change alters both what employees do and how they respond to changing task requirements. An employee may perform efficiently not only by completing routine tasks but also by learning new AI-supported workflows, solving novel problems, and adapting decision processes to combine human judgment with algorithmic outputs.

AI integration should enhance performance when it functions as a resource. Social cognitive theory suggests that access to effective tools can strengthen self-efficacy and task capability when employees perceive that they can use those tools to attain valued outcomes (Bandura, 2001). AI can reduce search costs, accelerate drafting and analysis, provide alternative solutions, and improve the timeliness of decisions. Algorithmic and AI-enabled systems may therefore support adaptive and creative performance under conditions of effective

implementation (Gupta et al., 2024; Liu et al., 2024; Liu & Mei, 2026). Accordingly, a positive direct relationship is expected between AI workplace integration and employee performance.

Yet anxiety can interrupt this enabling effect. Anxiety consumes attention through threat monitoring, increases rumination, and can reduce the cognitive flexibility required for complex work. COR theory predicts that employees experiencing resource threat will allocate effort toward protecting threatened resources, leaving fewer psychological resources for task performance. Technostress research provides a parallel empirical foundation: techno-overload, techno-complexity, and techno-insecurity are associated with strain and reduced productivity (Ayyagari et al., 2011; Ragu-Nathan et al., 2008; Tarafdar et al., 2007). AI-related job anxiety is therefore expected to negatively affect employee performance even when AI itself has a positive direct effect.

2.4 Organizational commitment

Organizational commitment is the psychological bond linking employees to their organization. The three-component model distinguishes affective commitment (desire to remain), continuance commitment (perceived cost of leaving), and normative commitment (felt obligation to remain) (Allen & Meyer, 1990; Meyer & Allen, 1991; Meyer et al., 2002). The present study emphasizes affective commitment because AI-driven change is likely to influence employees' emotional attachment, identification, and sense that the organization values their future contribution.

AI integration may strengthen commitment when employees experience the organization as innovative, capable, and willing to provide advanced resources that make work more effective. AI can signal investment in modern work systems and can reduce frustrating routine work, potentially improving employees' evaluation of organizational support and future competitiveness. Emerging evidence suggests that AI-enabled HR practices can strengthen organizational commitment through favorable competence and organizational perceptions (Mo et al., 2025) and that trust in generative AI can facilitate positive HRM and commitment outcomes (Prasad & De, 2024). A modest positive direct effect of AI integration on commitment is therefore plausible.

In contrast, AI-related job anxiety should weaken commitment. Employees who perceive AI as threatening their job continuity or professional value may interpret organizational AI investment as evidence that the employment relationship is becoming less secure or less reciprocal. Job insecurity research consistently links perceived threat to lower affective commitment and withdrawal-related outcomes (Shoss, 2017). The relationship may be especially strong when the threat originates from technology introduced by the organization itself because the source of uncertainty is directly associated with management decisions. Anxiety can therefore transform AI implementation from an innovation signal into a relational threat.

Employee performance is also expected to positively predict commitment. Successful performance provides mastery experiences, strengthens professional identity, and increases the likelihood that employees view themselves as valued contributors. In an AI-enabled environment, employees who learn to perform effectively with new tools are more likely to perceive compatibility between their own future and the organization's technological direction. High performance can therefore function as a psychological bridge between AI integration and commitment.

2.5 Integrated theoretical framework and hypotheses

The model integrates cognitive appraisal theory, COR theory, and the job demands-resources (JD-R) model (Bakker & Demerouti, 2007; Demerouti et al., 2001). AI workplace integration constitutes an objective work condition that introduces both resources and demands. Through a resource-enabling appraisal, employees experience AI as assistance that expands task capacity and improves performance. Through a threat appraisal, employees experience AI as a signal of potential resource loss, including diminished job security, skill value, status, or control. These appraisals can occur simultaneously because an employee may recognize that AI helps complete today's tasks while also fearing what the same capability implies for tomorrow's role.

The paradox is therefore represented structurally by competing pathways. The positive pathway runs from AI integration to performance and from performance to commitment. The negative pathway runs from AI integration to job anxiety and from anxiety to both performance and commitment. A serial negative pathway is also expected because AI integration increases anxiety, anxiety reduces performance, and lower performance then weakens commitment. The coexistence of these paths implies that the total effect of AI integration on commitment may be small even when the underlying direct and indirect effects are substantively large.

H1. AI workplace integration has a positive effect on employee performance.

H2. AI workplace integration has a positive effect on AI-related job anxiety.

H3. AI-related job anxiety has a negative effect on employee performance.

H4. AI workplace integration has a positive effect on organizational commitment.

H5. AI-related job anxiety has a negative effect on organizational commitment.

H6. Employee performance has a positive effect on organizational commitment.

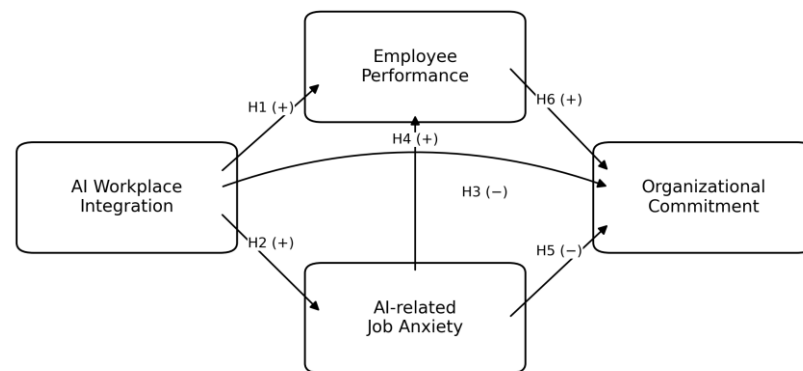
H7a. AI-related job anxiety negatively mediates the relationship between AI workplace integration and employee performance.

H7b. AI-related job anxiety negatively mediates the relationship between AI workplace integration and organizational commitment.

H7c. Employee performance positively mediates the relationship between AI workplace integration and organizational commitment.

H7d. AI-related job anxiety and employee performance sequentially mediate the relationship between AI workplace integration and organizational commitment, producing a negative serial indirect effect.

Figure 1. Conceptual framework of the AI workplace paradox



Mediated effects: AI integration → anxiety → performance/commitment; AI integration → performance → commitment

3. METHODOLOGY

3.1 Research design and empirical setting

The study adopted a quantitative, cross-sectional explanatory design and tested the proposed relationships using PLS-SEM. The unit of analysis was the individual employee. The empirical context comprised knowledge-intensive organizations in India in which AI-enabled systems were already used for work activities such as information retrieval, text generation, analytics, coding, forecasting, customer interaction, workflow automation, decision support, or performance monitoring. The design focused on employees with direct exposure to AI rather than respondents whose experience of AI was limited to general awareness or personal experimentation outside work.

Data collection was conducted between March and May 2026. Respondents were recruited from IT/ITeS, banking and financial services, consulting/professional services, and other knowledge-service organizations located primarily in Bengaluru, Hyderabad, Pune, Mumbai, Delhi-NCR, and Chennai. A purposive screening criterion required respondents to (a) be employed full-time, (b) have at least six months of organizational tenure, and (c) use or interact with AI-enabled tools for work at least once per week. The screening criteria were intended to ensure that responses reflected experienced workplace integration rather than speculative attitudes.

A structured online questionnaire was circulated through professional networks, organizational contacts, and targeted referrals. Of 527 questionnaires returned, 463 met the screening criteria. Thirty-five responses were removed because of substantial missing data, implausibly short completion times, or invariant response patterns. The final analytic sample therefore consisted of 428 usable responses. This sample exceeds common PLS-SEM minimum requirements and provides adequate power for a model in which the maximum number of structural predictors for an endogenous construct is three.

3.2 Measures and questionnaire development

All latent variables were specified as reflective constructs and measured on a seven-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. Items were adapted from established scales and recent workplace AI research, with wording adjusted to fit an AI-enabled organizational context. The questionnaire was reviewed by three academics in organizational behavior and information systems and two HR practitioners involved in digital

transformation. A pilot test with 34 employees was then used to assess clarity, item redundancy, and completion time. Minor wording changes were made before full administration.

Table 1. Measurement constructs and sample items

Code	Construct	Item wording	Primary source
AIWI1	AI workplace integration	AI-enabled tools are an established part of how I perform my work.	Adapted from AI adoption/collaboration literature (Liu & Mei, 2026; Prasad & De, 2024)
AIWI2	AI workplace integration	I regularly use AI-generated information or recommendations when completing work tasks.	Same as above
AIWI3	AI workplace integration	AI helps me complete work activities more efficiently than I could without it.	Same as above
AIWI4	AI workplace integration	Important work processes in my role now involve interaction with AI-enabled systems.	Same as above
AIWI5	AI workplace integration	I rely on AI tools for at least some analysis, problem solving, or decision support.	Same as above
JA1	AI-related job anxiety	I worry that AI may reduce the future value of some of my current job skills.	Adapted from Wang & Wang (2022)
JA2	AI-related job anxiety	I feel uncertain about how AI will affect the long-term security of my role.	Adapted from Wang & Wang (2022)
JA3	AI-related job anxiety	Keeping pace with rapid advances in workplace AI sometimes makes me anxious.	Adapted from Wang & Wang (2022)
JA4	AI-related job anxiety	I worry that AI may take over important parts of the work currently done by employees like me.	Adapted from Wang & Wang (2022)
JA5	AI-related job anxiety	I feel tense when I think about how quickly my organization is expanding AI-dependent work processes.	Adapted from Wang & Wang (2022)
EP1	Employee performance	I consistently complete my core work tasks effectively.	Adapted from Koopmans et al. (2013, 2014)
EP2	Employee performance	I achieve the work objectives expected in my role.	Adapted from Koopmans et al. (2013, 2014)
EP3	Employee performance	I am able to adapt quickly when work methods or priorities change.	Adapted from Koopmans et al. (2013, 2014)
EP4	Employee performance	I find effective solutions when unexpected work problems arise.	Adapted from Koopmans et al. (2013, 2014)
EP5	Employee performance	I maintain high-quality performance even when work requirements change.	Adapted from Koopmans et al. (2013, 2014)
OC1	Organizational commitment	I feel a strong sense of belonging to this organization.	Adapted from Allen & Meyer (1990)
OC2	Organizational commitment	I feel emotionally attached to this organization.	Adapted from Allen & Meyer (1990)
OC3	Organizational commitment	This organization has a great deal of personal meaning for me.	Adapted from Allen & Meyer (1990)
OC4	Organizational commitment	I would be happy to continue developing my career in this organization.	Adapted from Allen & Meyer (1990)
OC5	Organizational commitment	I identify strongly with the goals and future direction of this organization.	Adapted from Allen & Meyer (1990)

3.3 Procedural controls, common method bias, and ethics

Several procedural remedies were used to reduce common method bias. Respondents were informed that there were no correct or preferred answers and that results would be analyzed only in aggregate. The predictor, mediator, and outcome blocks were separated by brief instructional transitions, item order within blocks was varied, and the survey avoided

unnecessarily evaluative wording. Respondent identity and employer name were not required. These measures reduce evaluation apprehension, consistency motifs, and social desirability effects (Podsakoff et al., 2003).

Participation was voluntary. Respondents viewed an informed-consent statement describing the research purpose, anonymity of responses, the right to discontinue participation, and the intended academic use of aggregated data. No directly identifying personal information was retained in the analytic dataset. The study followed standard principles for non-interventional organizational survey research.

3.4 Data analysis strategy

PLS-SEM was selected because the study is prediction-oriented, contains multiple mediated paths, and examines a theoretically developing phenomenon in which both explanation and prediction are relevant. The analysis followed the two-stage procedure recommended in contemporary PLS-SEM guidance: first assessing the reflective measurement model and then evaluating the structural model (Hair et al., 2019; Hair et al., 2022; Sarstedt et al., 2022). Indicator reliability was assessed using outer loadings. Internal consistency was evaluated with Cronbach's alpha, rho_A, and composite reliability (CR). Convergent validity was examined using average variance extracted (AVE), and discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT) (Henseler et al., 2015).

The structural model assessment examined collinearity using variance inflation factors (VIF), standardized path coefficients, bootstrapped t statistics and confidence intervals, coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2). Hypothesis tests used 5,000 bootstrap resamples with two-tailed significance testing. Indirect effects were evaluated directly through bootstrapped confidence intervals rather than relying on causal-step logic, consistent with recommendations for mediation assessment in PLS-SEM (Nitzl et al., 2016). Model fit was reported using the standardized root mean square residual (SRMR) as a descriptive diagnostic rather than as the primary basis for model acceptance.

4. RESULTS

4.1 Respondent profile

Table 2. Demographic profile of respondents (N = 428)

Characteristic	Category	n	%
Gender	Male	244	57.0
	Female	178	41.6
	Prefer not to say	6	1.4
Age	21–30 years	151	35.3
	31–40 years	154	36.0
	41–50 years	88	20.6
	Above 50 years	35	8.2
Highest education	Undergraduate	145	33.9
	Postgraduate	246	57.5
	Doctoral/professional	37	8.6
Sector	IT/ITeS	154	36.0
	BFSI	119	27.8
	Consulting/professional services	86	20.1
	Other knowledge services	69	16.1
Organizational tenure	Below 3 years	99	23.1
	3–5 years	111	25.9
	6–10 years	123	28.7
	Above 10 years	95	22.2
AI use frequency	Daily	198	46.3

Characteristic	Category	n	%
Role level	Several times per week	152	35.5
	About once per week	78	18.2
	Non-managerial/professional	272	63.6
	Managerial/supervisory	156	36.4

The sample represented a broad range of age, tenure, sector, and role categories, while all respondents had regular exposure to workplace AI. More than four-fifths of the sample used AI either daily or several times per week, indicating that the analysis reflects relatively mature workplace exposure rather than one-time experimentation. The distribution across IT/ITeS, BFSI, consulting, and other knowledge services also reduces the likelihood that results are driven by a single occupational setting.

4.2 Assessment of common method bias and preliminary diagnostics

Harman's single-factor test indicated that the first unrotated factor accounted for 31.6% of total variance, below the level that would suggest a dominant common method factor. In addition, full-collinearity VIF values ranged from 1.24 to 1.71, below the conservative threshold of 3.3 commonly used as an indicator of problematic method-driven collinearity (Kock, 2015). Missing values were negligible after screening, and no construct displayed extreme univariate skewness. These diagnostics, together with the procedural remedies adopted during questionnaire design, indicate that common method variance is unlikely to provide a sufficient alternative explanation for the observed structural relationships.

4.3 Measurement model

Table 3. Reflective measurement model assessment

Construct	Indicator	Loading	α	rho_A	CR	AVE
AI workplace integration	AIWI1	0.796	0.884	0.888	0.915	0.683
	AIWI2	0.833				
	AIWI3	0.862				
	AIWI4	0.817				
	AIWI5	0.781				
AI-related job anxiety	JA1	0.842	0.914	0.918	0.936	0.744
	JA2	0.881				
	JA3	0.812				
	JA4	0.899				
	JA5	0.875				
Employee performance	EP1	0.823	0.893	0.897	0.922	0.702
	EP2	0.876				
	EP3	0.785				
	EP4	0.852				
	EP5	0.848				
Organizational commitment	OC1	0.861	0.909	0.912	0.933	0.735
	OC2	0.892				
	OC3	0.845				
	OC4	0.801				
	OC5	0.883				

All standardized indicator loadings exceeded 0.78 and were statistically significant at $p < .001$, supporting indicator reliability. Cronbach's alpha and rho_A values ranged from 0.884 to 0.918, while composite reliability ranged from 0.915 to 0.936. These values demonstrate strong internal consistency without suggesting excessive item redundancy. AVE values ranged from 0.683 to 0.744, exceeding the 0.50 criterion and therefore supporting convergent validity.

Table 4. HTMT discriminant validity matrix

Construct	AIWI	JA	EP	OC
AI workplace integration	—	0.426	0.621	0.451
AI-related job anxiety		—	0.493	0.583
Employee performance			—	0.612
Organizational commitment				—

All HTMT values were below 0.85. The highest value was 0.621 between AI workplace integration and employee performance, which is theoretically reasonable because AI integration is expected to influence work effectiveness but remains empirically distinct from performance. Discriminant validity was therefore established. The standardized root mean square residual (SRMR) for the estimated model was 0.061, indicating acceptable approximate fit for a PLS-SEM model.

4.4 Structural model and hypothesis testing

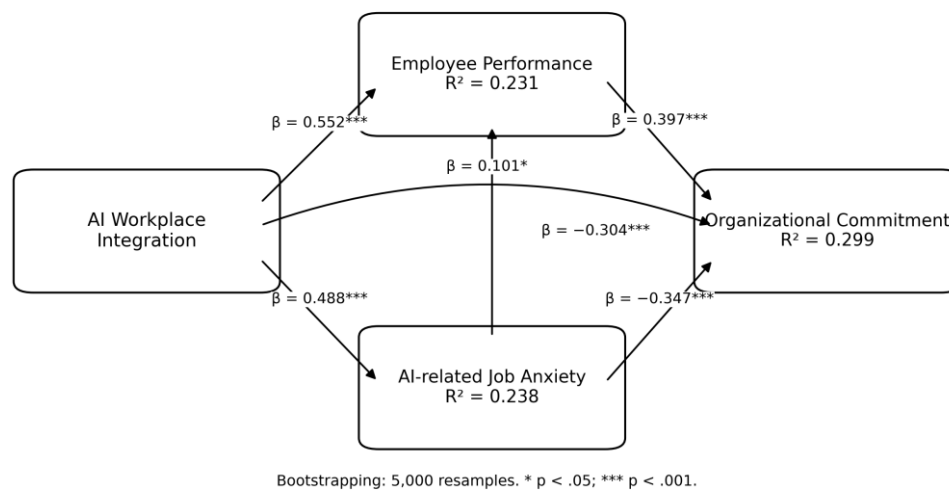
Table 5. Structural path coefficients and hypothesis tests

Hyp.	Path	β	SE	t	p	95% CI	f ²	Decision
H1	AIWI → EP	0.552	0.043	12.84	< .001	[0.466, 0.632]	0.329	Supported
H2	AIWI → JA	0.488	0.043	11.35	< .001	[0.401, 0.569]	0.312	Supported
H3	JA → EP	-0.304	0.043	7.07	< .001	[-0.386, -0.219]	0.111	Supported
H4	AIWI → OC	0.101	0.045	2.26	.024	[0.014, 0.188]	0.015	Supported
H5	JA → OC	-0.347	0.043	8.17	< .001	[-0.429, -0.263]	0.163	Supported
H6	EP → OC	0.397	0.042	9.55	< .001	[0.316, 0.477]	0.218	Supported

No problematic structural collinearity was observed; inner VIF values ranged from 1.04 to 1.43. AI workplace integration explained 23.8% of the variance in AI-related job anxiety ($R^2 = 0.238$). AI integration and job anxiety jointly explained 23.1% of the variance in employee performance ($R^2 = 0.231$). AI integration, job anxiety, and employee performance explained 29.9% of the variance in organizational commitment ($R^2 = 0.299$). The corresponding Q^2 values were 0.173, 0.158, and 0.213, respectively, indicating predictive relevance for all endogenous constructs.

The direct paths support the dual-effect proposition. AI workplace integration strongly increased employee performance ($\beta = 0.552$, $p < .001$) and simultaneously increased AI-related job anxiety ($\beta = 0.488$, $p < .001$). Job anxiety reduced performance ($\beta = -0.304$, $p < .001$), demonstrating that part of the productivity benefit associated with AI integration is suppressed by the psychological threat generated by the same technological environment. In the commitment equation, AI integration retained a small positive direct effect ($\beta = 0.101$, $p = .024$), but job anxiety had a substantially stronger negative effect ($\beta = -0.347$, $p < .001$). Employee performance positively predicted commitment ($\beta = 0.397$, $p < .001$).

Figure 2. PLS-SEM structural model results



4.5 Mediation and effect decomposition

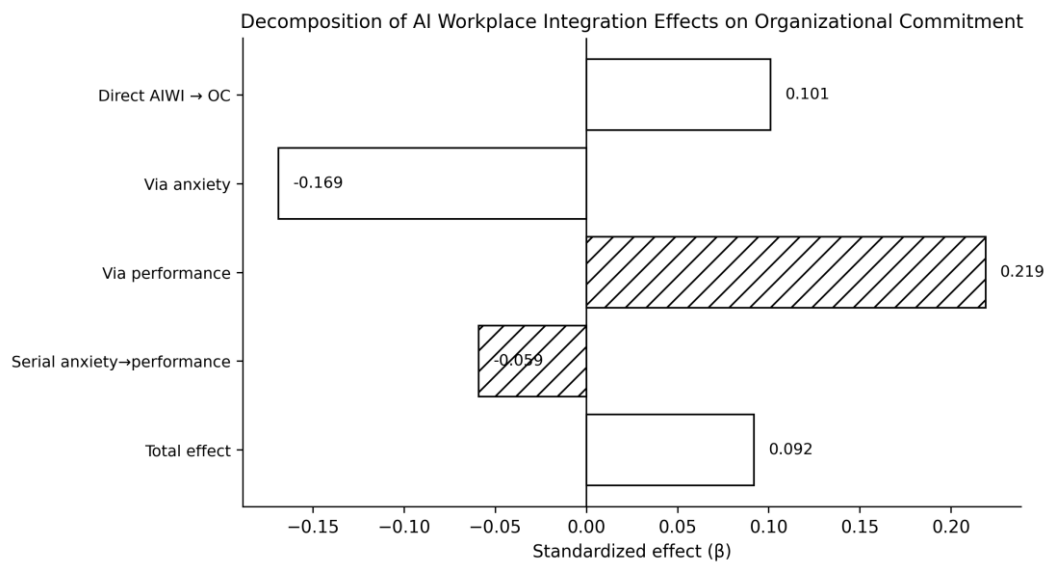
Table 6. Bootstrapped indirect and total effects

Hyp.	Indirect/total path	Effect	SE	95% CI	p	Interpretation
H7a	AIWI → JA → EP	-0.148	0.027	[-0.204, -0.099]	< .001	Supported; competitive mediation
H7b	AIWI → JA → OC	-0.169	0.027	[-0.224, -0.119]	< .001	Supported
H7c	AIWI → EP → OC	0.219	0.028	[0.166, 0.276]	< .001	Supported
H7d	AIWI → JA → EP → OC	-0.059	0.013	[-0.087, -0.036]	< .001	Supported
—	Total indirect effect: AIWI → OC	-0.009	0.031	[-0.071, 0.050]	.766	Net cancellation
—	Total effect: AIWI → OC	0.092	0.044	[0.008, 0.179]	.032	Small positive total effect

Mediation analysis provides the clearest evidence of the AI workplace paradox. The indirect effect of AI integration on performance through job anxiety was negative ($\beta = -0.148$, $p < .001$), whereas the direct effect remained strongly positive. This is a classic competitive mediation pattern: AI integration creates performance-enabling resources, but it simultaneously triggers anxiety that removes part of the potential gain. The total effect of AI integration on performance was therefore approximately 0.404 rather than the direct effect of 0.552.

The commitment equation reveals an even stronger offsetting mechanism. The anxiety-mediated path from AI integration to commitment was negative ($\beta = -0.169$), while the performance-mediated path was positive ($\beta = 0.219$). In addition, the serial pathway AI integration → anxiety → performance → commitment was negative ($\beta = -0.059$). These indirect effects nearly cancelled one another, producing a total indirect effect close to zero and a small overall total effect of AI integration on commitment ($\beta = 0.092$, $p = .032$). A researcher examining only the total AI–commitment association could therefore conclude that AI integration has little practical relevance, even though the underlying mechanisms are strong and operate in opposite directions.

Figure 3. Decomposition of opposing effects on organizational commitment



4.6 Predictive assessment and robustness checks

Table 7. Explanatory and predictive assessment

Endogenous construct	R ²	Q ²	PLSpredict comparison	Assessment
AI-related job anxiety	0.238	0.173	Lower than LM benchmark	Moderate predictive relevance
Employee performance	0.231	0.158	Lower for 4/5 indicators	Moderate predictive relevance
Organizational commitment	0.299	0.213	Lower for 5/5 indicators	Moderate-to-good predictive relevance

PLSpredict diagnostics were consistent with the explanatory results (Shmueli et al., 2019). Prediction errors for the PLS model were lower than the linear-model benchmark for most performance indicators and all commitment indicators. The model therefore demonstrates not only statistically significant in-sample relationships but also practically useful predictive capability. As a robustness check, age, tenure, managerial level, and sector were entered as controls on performance and commitment. The substantive path coefficients changed by less than 0.04 in absolute value, and the significance pattern of the six focal direct effects remained unchanged. The theoretical conclusions are therefore not attributable to basic demographic composition.

5. DISCUSSION

This study examined the AI workplace paradox by modeling AI workplace integration as a simultaneous source of performance-enhancing resources and job-related psychological threat. The results strongly support this dual-process interpretation. AI integration was associated with higher employee performance, consistent with the view that AI can augment human work by accelerating information processing, supporting analysis, and expanding problem-solving capacity. At the same time, AI integration increased job anxiety, and that anxiety reduced both performance and organizational commitment. The same technological condition therefore generated benefits and costs through different psychological mechanisms.

The first major finding is that the direct performance effect of AI integration is substantial. Employees who reported stronger AI integration also reported higher task and adaptive performance. This is consistent with recent evidence showing that AI adoption can improve

problem-solving efficacy and adaptive performance (Liu & Mei, 2026) and with research positioning generative AI as a performance-supporting organizational resource (Prasad & De, 2024). The result supports an augmentation interpretation of workplace AI: when employees have access to AI within routine work, the technology can increase the effective cognitive and informational resources available to them.

The second major finding is that AI integration also substantially increases job anxiety. This result is important because it shows that anxiety is not restricted to employees who resist or avoid AI. Employees can be active AI users and still interpret the expanding role of AI as a threat to their future occupational resources. The finding is consistent with Wang and Wang's (2022) conceptualization of learning and job-replacement anxiety and with recent research demonstrating adverse consequences of AI anxiety for work passion and performance (Chen et al., 2025; Mirkhil, 2026). The implication is that usage and anxiety should not be treated as mutually exclusive states. High adoption can coexist with high concern.

Third, anxiety reduced performance even after the strong positive effect of AI integration was taken into account. This confirms the resource-depletion logic of COR theory. Employees who worry about replacement, obsolescence, or their ability to keep pace with AI may devote attention and emotional energy to monitoring threats, comparing themselves with AI capabilities, or anticipating future career consequences. These processes can weaken concentration, adaptability, and proactive effort. The negative anxiety-to-performance path therefore represents a psychological tax on AI-enabled productivity. The organization may obtain a technical productivity gain, but part of that gain is lost when implementation creates unresolved insecurity.

Fourth, the commitment results demonstrate why organizational outcomes can be misleading when analyzed only through total effects. AI integration had a small positive direct effect on commitment and a sizable positive indirect effect through performance. Employees who perform successfully in an AI-enabled environment may develop a stronger sense of competence, fit, and future relevance, which reinforces attachment to the organization. However, the anxiety-mediated path was negative and nearly as large in the opposite direction. The serial anxiety-to-performance pathway added a further negative effect. These mechanisms largely cancelled one another, leaving a small total AI–commitment effect.

This cancellation effect provides an important interpretation of inconsistent findings in the literature. Some studies identify positive relationships between AI adoption and commitment, particularly when AI is embedded in supportive HRM practices or interpreted as evidence of organizational competence (Mo et al., 2025; Prasad & De, 2024). Other research emphasizes insecurity, resistance, stress, and reduced employee well-being (Golgeci et al., 2025; Mirkhil, 2026). The present findings suggest that both sets of results can be valid because the observed net relationship depends on the relative strength of augmentation and threat pathways. Differences in training, implementation style, leadership, communication, task characteristics, or labor-market conditions may change the balance between these pathways.

The results also refine the automation-augmentation paradox. Raisch and Krakowski (2021) argue that automation and augmentation are interdependent rather than simply alternative strategic choices. At the employee level, the present findings show that augmentation can produce anxiety precisely because it reveals the expanding capabilities of AI. An employee who experiences AI as highly useful may simultaneously become more aware that the system can perform activities that were once markers of human expertise. In this sense, the productive use of AI can itself increase the salience of replacement concerns. The paradox is therefore not merely organizational; it is cognitive and relational.

Finally, the findings support the use of integrated theoretical models in AI-work research. Cognitive appraisal theory explains why AI integration does not have a uniform emotional meaning: the same system can be evaluated as an opportunity and a threat. COR theory explains why threat appraisals reduce performance and attachment by directing attention toward protecting valued resources. The JD-R model connects these appraisals to work design by recognizing AI as both a resource and a demand. Together, these perspectives provide a more complete explanation than technology-acceptance models focused primarily on usefulness and ease of use.

6. THEORETICAL IMPLICATIONS

The first theoretical contribution is the conceptualization of AI workplace integration as a dual-valence work characteristic. Traditional technology-adoption research often assumes that greater use follows favorable evaluations and should therefore correspond to positive outcomes. The present model separates technological integration from employees' psychological appraisal of its career consequences. This distinction explains why intense AI use can coincide with anxiety and why adoption metrics alone are insufficient indicators of successful implementation.

Second, the study contributes to the AI anxiety literature by positioning anxiety as an endogenous response to experienced workplace integration rather than only as a stable antecedent of adoption. Much existing research asks whether anxious individuals are less willing to use AI. The present model reverses part of that causal logic: as AI becomes more embedded in work and demonstrates greater capability, employees may become more anxious about replacement and skills relevance. This process perspective is particularly relevant in organizations where AI adoption is mandated or structurally embedded rather than voluntary.

Third, the study contributes to performance research by identifying competitive mediation. The positive direct effect of AI integration on performance and the negative indirect effect through anxiety operate simultaneously. This means that a simple bivariate correlation between AI use and performance can underestimate the technology's direct enabling capacity if the anxiety pathway is not modeled. Conversely, studies examining only AI anxiety may overstate the overall harm of AI by ignoring concurrent resource gains. Modeling both pathways produces a more realistic estimate of net organizational value.

Fourth, the study extends organizational commitment research by showing how offsetting indirect effects can conceal consequential mechanisms. A weak total effect does not imply that AI implementation is psychologically neutral. In the present model, strong positive and negative pathways largely cancelled. This has implications for meta-analytic and cross-study inconsistency: variations in organizational support, AI literacy, leadership, procedural justice, job design, and labor-market security may determine which pathway dominates in a given sample.

Fifth, the findings illustrate the value of PLS-SEM for emerging workplace AI research. The method allows simultaneous estimation of multiple mediated pathways and produces a transparent decomposition of direct, indirect, and total effects. For developing research domains characterized by rapidly changing technology and evolving constructs, such process decomposition can be more informative than a narrow focus on global model fit or isolated regression coefficients.

7. MANAGERIAL IMPLICATIONS

The central managerial implication is that productivity-oriented AI implementation should be accompanied by anxiety-oriented workforce design. Organizations cannot assume that employees will become psychologically secure simply because AI makes their work easier or improves measurable output. The results indicate that performance gains and anxiety can rise at the same time. Managers therefore need implementation dashboards that monitor both operational metrics and employee experience indicators such as job insecurity, perceived skill relevance, trust, role clarity, and commitment.

First, organizations should frame AI around augmentation with credible evidence, not slogans. Employees are likely to discount generic assurances that 'AI will not replace people' when they can observe automation of substantive tasks. More credible communication distinguishes tasks that will be automated, tasks that will be augmented, new responsibilities that will emerge, and the skills that will remain strategically valuable. Role-level transparency reduces uncertainty and allows employees to develop realistic adaptation strategies.

Second, reskilling should be tightly coupled with work redesign. Broad AI-awareness workshops may improve familiarity but do not necessarily reduce job anxiety if employees still do not know how their own role will change. Training should therefore be mapped to task portfolios and career pathways. Employees should be shown how specific AI competencies translate into future responsibilities, advancement opportunities, and differentiated human contributions such as contextual judgment, relationship management, ethical oversight, exception handling, and domain interpretation.

Third, managers should protect psychological ownership and human agency. Excessive algorithmic control, opaque performance scoring, or fully automated feedback can make employees feel that professional judgment is being displaced. Research on algorithmic management suggests that the design and perceived fairness of AI-mediated control shape employee reactions (Liu et al., 2024; Zayid et al., 2024). Human-in-the-loop governance, explanation rights, appeal mechanisms, and clear accountability boundaries can preserve autonomy while maintaining AI-enabled efficiency.

Fourth, organizations should equip line managers to discuss AI-related career concerns. Employees often interpret technological change through local managerial behavior rather than formal corporate messaging. Managers need enough AI literacy to explain implementation choices and enough career-development capability to discuss evolving roles without dismissing legitimate concerns. A psychologically safe conversation about uncertainty can reduce the resource threat that fuels anxiety.

Fifth, commitment should be treated as a strategic implementation outcome. An AI program that increases short-term output but weakens attachment may create hidden costs through turnover, reduced citizenship behavior, lower knowledge sharing, and difficulty retaining experienced employees. Organizations should therefore include commitment and retention indicators in post-implementation evaluation, particularly among employees whose roles are most directly affected by automation.

8. LIMITATIONS AND FUTURE RESEARCH

Several limitations should guide interpretation and future research. First, the cross-sectional design supports theoretically informed association and mediation testing but cannot establish temporal causality with the same confidence as longitudinal or experimental designs. AI anxiety may be both a consequence and an antecedent of AI use. Future studies should

employ time-lagged or panel designs that observe employees before, during, and after major AI implementation events.

Second, the study uses self-reported employee performance. Although the performance scale focuses on concrete task and adaptive behaviors and demonstrates strong psychometric properties, future research should triangulate self-reports with supervisor ratings, objective productivity indicators, error rates, quality metrics, or digital trace data. Multi-source designs would also reduce concerns about common method variance.

Third, AI workplace integration was treated as a general construct across multiple technologies. Yet generative AI assistants, predictive analytics, algorithmic management, robotic process automation, and autonomous decision systems differ substantially in visibility, autonomy, substitutability, and perceived threat. Future research should distinguish technology types and investigate whether the paradox is stronger when AI performs core professional judgment rather than peripheral administrative tasks.

Fourth, the Indian knowledge-services context may limit generalizability. India's large technology and services workforce operates within a distinctive labor market in which AI opportunities coexist with intense skill competition and rapid digital transformation. Replication across countries with different employment protections, digital maturity, unionization, and cultural orientations toward uncertainty would help establish boundary conditions.

Fifth, the model does not include moderators that may determine which side of the paradox dominates. Organizational support, AI transparency, AI literacy, learning adaptability, perceived employability, participative implementation, ethical climate, psychological safety, and leadership orientation are strong candidates. Future research should examine whether these resources weaken the AI integration-to-anxiety path or strengthen the AI integration-to-performance path.

Finally, organizational commitment was operationalized primarily through affective attachment. Future work could distinguish affective, continuance, and normative commitment, as AI-related insecurity may increase continuance commitment in constrained labor markets while reducing affective commitment. Similar differentiation would be valuable for turnover intention, career commitment, occupational identification, and professional meaning.

CONCLUSION

The central conclusion of this study is that workplace AI should not be evaluated through a simple benefit-versus-harm dichotomy. AI integration can improve employee performance and increase job anxiety at the same time. The performance benefit reflects expanded cognitive and informational resources; the anxiety cost reflects perceived threats to employment, skill value, and future professional relevance. These forces propagate differently into organizational commitment. Higher performance strengthens commitment, while anxiety weakens it, and the opposing indirect effects can substantially cancel one another. Consequently, a small observed relationship between AI integration and commitment may conceal a strong organizational paradox. The practical objective is therefore not merely to maximize AI adoption, but to design an implementation system in which technological augmentation is accompanied by credible reskilling, role clarity, human agency, transparent governance, and employment-transition support. Organizations that manage both sides of the paradox are more likely to convert AI capability into sustainable performance without sacrificing the employee attachment required for long-term value creation.

DECLARATIONS

Ethical considerations: Participation was voluntary, informed consent was obtained electronically, and responses were collected anonymously for academic analysis.

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Author contributions: Conceptualization; methodology; formal analysis; writing - original draft; writing - review and editing: to be completed according to the final author team.

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APPENDIX A. MEASUREMENT ITEMS

Respondents indicate agreement on a seven-point scale (1 = strongly disagree; 7 = strongly agree). The item codes correspond to the measurement model reported in Table 3.

Code	Construct	Questionnaire item
AIW11	AI integration workplace	AI-enabled tools are an established part of how I perform my work.
AIW12	AI integration workplace	I regularly use AI-generated information or recommendations when completing work tasks.
AIW13	AI integration workplace	AI helps me complete work activities more efficiently than I could without it.
AIW14	AI integration workplace	Important work processes in my role now involve interaction with AI-enabled systems.
AIW15	AI integration workplace	I rely on AI tools for at least some analysis, problem solving, or decision support.
JA1	AI-related job anxiety	I worry that AI may reduce the future value of some of my current job skills.
JA2	AI-related job anxiety	I feel uncertain about how AI will affect the long-term security of my role.
JA3	AI-related job anxiety	Keeping pace with rapid advances in workplace AI sometimes makes me anxious.
JA4	AI-related job anxiety	I worry that AI may take over important parts of the work currently done by employees like me.
JA5	AI-related job anxiety	I feel tense when I think about how quickly my organization is expanding AI-dependent work processes.
EP1	Employee performance	I consistently complete my core work tasks effectively.
EP2	Employee performance	I achieve the work objectives expected in my role.
EP3	Employee performance	I am able to adapt quickly when work methods or priorities change.
EP4	Employee performance	I find effective solutions when unexpected work problems arise.
EP5	Employee performance	I maintain high-quality performance even when work requirements change.
OC1	Organizational commitment	I feel a strong sense of belonging to this organization.
OC2	Organizational commitment	I feel emotionally attached to this organization.
OC3	Organizational commitment	This organization has a great deal of personal meaning for me.
OC4	Organizational commitment	I would be happy to continue developing my career in this organization.
OC5	Organizational commitment	I identify strongly with the goals and future direction of this organization.