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Psychological Predictors of Employee Adaptation to Artificial Intelligence in the Workplace

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ABSTRACT: Organizations are increasingly integrating artificial intelligence (AI) into routine work processes, fundamentally reshaping how employees perform tasks, make decisions, and interact with emerging technologies. However, employees differ considerably in their capacity to adapt to AI driven workplace transformation, highlighting the importance of understanding the psychological mechanisms underlying successful adaptation. This study investigated the psychological determinants of employee adaptation to AI by integrating AI self efficacy, AI anxiety, psychological capital, perceived organizational support, and openness to experience within a unified theoretical framework. A cross sectional survey design was employed, and hierarchical multiple regression and bootstrapped mediation analyses were conducted to examine the proposed relationships. The results demonstrated that AI self efficacy, psychological capital, and perceived organizational support positively predicted employee adaptation to AI, whereas AI anxiety negatively predicted adaptation. Psychological capital further partially mediated the relationship between AI anxiety and employee adaptation, indicating that positive psychological resources may reduce, although not eliminate, the adverse influence of AI related anxiety. These findings extend the Job Demands Resources framework to AI driven organizational transformation by demonstrating how technology related demands and personal and organizational resources jointly contribute to employee adaptation. The study further highlights psychological capital as an important mechanism connecting AI related anxiety with adaptive workplace outcomes. From a practical perspective, organizations should complement technical AI training with interventions that strengthen employees' confidence, resilience, optimism, psychological readiness, and perceptions of organizational support. Such an integrated approach may facilitate more sustainable employee adaptation and reduce psychological barriers during AI implementation.

KEYWORDS: Artificial intelligence; employee adaptation; AI anxiety; AI self-efficacy; psychological capital; organizational psychology

1. Introduction

The accelerating diffusion of artificial intelligence (AI) across organizational settings is fundamentally transforming how employees perform, coordinate, evaluate, and experience their work. Generative AI, algorithmic decision support systems, and intelligent automation are no longer confined to specialized technical functions but are increasingly incorporated into

routine administrative, analytical, managerial, and creative activities across industries [1, 2]. As organizations expand their reliance on these technologies, successful AI implementation increasingly depends not only on technological capability but also on employees' capacity and willingness to adapt to AI mediated work environments. Consequently, understanding why some employees respond constructively to AI driven change while others experience anxiety, resistance, uncertainty, or disengagement has become an important issue in organizational psychology and human resource management [3, 4].

Employee adaptation to AI can be conceptualized as the extent to which individuals adjust their attitudes, competencies, and work behaviors to function effectively in environments where AI technologies are integrated into existing or emerging work processes. This adaptation extends beyond the acquisition of technical skills. Unlike earlier forms of workplace automation that predominantly affected routine and manual activities, contemporary AI increasingly intersects with cognitive, analytical, creative, and judgment based tasks [2, 5]. Employees may therefore need to reconsider established work practices, develop new competencies, and adjust perceptions of professional autonomy, occupational identity, and personal value within increasingly AI augmented work environments [6, 9]. Adaptation to AI should thus be understood as both a technological and psychological process.

Among the psychological factors associated with this process, AI anxiety has emerged as an important potential barrier. AI anxiety refers broadly to apprehension, uncertainty, or concern associated with interacting with AI technologies or with their potential implications for employment and professional roles [1, 4, 10−14]. Previous studies have associated AI related anxiety with lower technology adoption intentions, reduced job satisfaction, and heightened perceptions of job insecurity [2, 3, 13]. These findings suggest that the psychological demands created by AI implementation may inhibit employees' willingness or ability to engage constructively with technological change. However, the influence of AI anxiety may depend substantially on the personal and organizational resources available to employees.

AI self efficacy represents one such resource. It reflects employees' confidence in their ability to understand, interact with, and effectively use AI technologies in their work. Employees with stronger AI self efficacy may be more willing to experiment with unfamiliar technologies, persist when encountering difficulties, and incorporate AI tools into established work routines. Previous evidence has linked technology related self efficacy with stronger adoption intentions and innovative work behavior, particularly under conditions characterized by technological uncertainty and rapid change [5, 6, 11]. AI self efficacy may therefore provide an important cognitive resource that enables employees to approach AI as a manageable workplace tool rather than primarily as a source of uncertainty or threat.

Psychological capital provides a broader positive psychological resource that may further facilitate adaptation. Psychological capital incorporates self efficacy, hope, resilience, and optimism as interconnected psychological capacities that enable individuals to respond constructively to workplace demands and adversity. Within AI driven organizational change, employees with stronger psychological capital may be better equipped to recover from technological difficulties, maintain positive expectations regarding change, identify alternative strategies when encountering challenges, and remain engaged despite uncertainty. Psychological capital has consequently been proposed as an important resource for reducing AI induced strain and promoting constructive engagement with technological transformation

[9, 12]. Importantly, its role may extend beyond a direct association with adaptation by providing a psychological mechanism through which the adverse influence of AI anxiety is reduced.

Employee adaptation may also depend on organizational and dispositional resources. Perceived organizational support reflects employees' beliefs regarding the extent to which their organization values their contributions and supports their well being. During AI implementation, such support may be particularly important because employees often require training, communication, managerial guidance, and reassurance regarding changing roles and expectations. Organizational support may therefore influence whether AI transformation is interpreted primarily as a developmental opportunity or as an unmanaged organizational threat [10, 12]. At the individual level, openness to experience may also facilitate adaptation because employees who are receptive to novelty, experimentation, and new ideas may respond more constructively to technological change. Previous studies have identified openness to experience as an important predictor of technology acceptance and innovative behavior in AI related contexts [6−8].

These psychological and organizational factors can be conceptually integrated through the Job Demands Resources (JD R) framework. The framework distinguishes between demands that require sustained psychological or behavioral effort and resources that support goal achievement, personal development, and effective responses to workplace demands. Within the context of AI driven organizational transformation, AI anxiety can be conceptualized as a psychological demand that may impede adaptation, whereas AI self efficacy, psychological capital, perceived organizational support, and openness to experience represent personal or contextual resources that may facilitate constructive adjustment [9, 12]. From this perspective, successful adaptation depends not merely on reducing AI related demands but also on strengthening the psychological and organizational resources employees can mobilize when responding to technological change.

Despite growing research on employee responses to AI, an important empirical gap remains. Previous studies have frequently examined AI anxiety, self efficacy, personality, psychological resources, or organizational support separately or within specific occupational contexts [4, 11, 14]. Consequently, their relative contributions to employee adaptation remain insufficiently understood when these factors are considered simultaneously. More importantly, relatively limited attention has been directed toward the psychological mechanisms through which AI related anxiety translates into adaptive or maladaptive workplace outcomes. Establishing whether psychological capital functions as an intervening mechanism is theoretically important because it may explain why employees experiencing similar levels of AI anxiety nevertheless differ in their capacity to adapt successfully. This distinction also has practical relevance because psychological resources may be more amenable to organizational intervention than relatively stable dispositional characteristics.

Accordingly, this study aimed to determine how AI related psychological demands and personal and organizational resources jointly shape employee adaptation to AI, with particular attention to the mediating role of psychological capital in the relationship between AI anxiety and adaptation. By integrating AI self efficacy, AI anxiety, psychological capital, perceived organizational support, and openness to experience within a unified JD R based model, this study provides a more comprehensive account of the psychological processes underlying adaptation to AI driven workplace transformation and offers an empirical foundation for

organizational strategies designed to strengthen workforce readiness, psychological resilience, and sustainable human AI collaboration.

2. Materials and Methods

2.1. Research Design.

This study employed a cross sectional, correlational survey design to examine the psychological factors associated with employee adaptation to artificial intelligence (AI) in the workplace. Data were collected at a single time point using a self administered online questionnaire. This design enabled the simultaneous assessment of multiple psychological and organizational factors and their associations with employee adaptation to AI, consistent with previous organizational psychology research examining technology adoption and employee responses to technological change [6, 8, 11]. Given the observational and cross sectional nature of the study, the analyses were intended to identify associations and predictive relationships rather than establish causal effects.

2.2. Participants and Sampling.

Participants were full time employees working in organizations that had implemented at least one AI based technology, including generative AI applications, algorithmic decision support systems, or intelligent automation software, within their routine work processes during the preceding 12 months. A nonprobability purposive sampling strategy supplemented by snowball recruitment through professional networks was employed to identify eligible participants across multiple industry sectors. This recruitment approach was consistent with sampling procedures used in comparable studies of workplace AI adoption [3, 14]. Participants were eligible if they had worked in their current organization for at least six months and had direct or indirect exposure to AI based technologies as part of their regular work responsibilities. The minimum sample size was determined *a priori* using G*Power for a multiple regression model with five predictors. Assuming a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = .05$, and statistical power of .95, the analysis indicated a minimum required sample of 138 participants. The recruitment target was set above this minimum requirement to account for potentially incomplete or invalid responses and to provide sufficient observations for the planned multivariable analyses.

2.3. Measures.

AI self efficacy was assessed using a multi item measure capturing employees' confidence in their ability to learn, operate, and address difficulties associated with AI based technologies in their occupational roles [5, 6]. Items were rated on a six point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*), with higher scores representing greater perceived capability to use AI effectively.

AI anxiety was measured using an adapted version of the Artificial Intelligence Anxiety Scale. The measure assessed apprehension associated with AI, including concerns regarding job displacement, difficulties in learning or interacting with AI technologies, and broader sociotechnical consequences of workplace AI implementation [1, 4]. Items were rated on a six point Likert scale, with higher scores indicating greater AI related anxiety.

Psychological capital was assessed using items representing its four core dimensions: self efficacy, hope, resilience, and optimism. These dimensions collectively reflected employees' positive psychological resources for responding constructively to workplace demands and technological change. Items were rated on a six point Likert scale, consistent with previous applications of psychological capital in AI related organizational research [9, 12].

Perceived organizational support for AI adaptation was assessed using items measuring the extent to which employees perceived that their organization provided adequate training, resources, guidance, and encouragement to facilitate adjustment to AI related workplace changes [10]. Responses were recorded on a six point Likert scale, with higher scores indicating stronger perceived organizational support.

Openness to experience was assessed using items derived from a Big Five personality inventory and adapted to the context of workplace technology adoption. The measure captured employees' receptiveness to novelty, new ideas, experimentation, and changes in established work practices [6, 7, 8]. Items were rated on a six point Likert scale, with higher scores indicating greater openness to experience.

Employee adaptation to AI represented the primary outcome variable and was assessed using items capturing behavioral and attitudinal adjustment to AI augmented work environments. The measure encompassed willingness to modify established work routines, proactively acquire AI related competencies, and adjust to workflows incorporating AI technologies [2, 11]. Items were rated on a six point Likert scale, with higher scores representing stronger adaptation to AI integrated work processes. Demographic and organizational characteristics, including age, gender, educational attainment, industry sector, and organizational tenure, were also collected and considered as covariates in the multivariable analyses.

2.4. Data Collection Procedure.

The questionnaire was administered electronically to eligible participants. Before accessing the survey, participants were provided with an informed consent statement describing the study purpose, voluntary nature of participation, anonymity of responses, and their right to withdraw from the study at any time without penalty. Only participants who provided informed consent proceeded to the questionnaire. Data collection continued until the predetermined recruitment target was achieved. Attention check items were embedded within the questionnaire to identify potentially inattentive or low quality responses. Participants who failed more than one attention check were excluded before statistical analysis. Eligible responses were subsequently screened for completeness and suitability for inclusion in the final analytic dataset.

2.5. Data Analysis.

Data were analyzed using standard statistical software. Descriptive statistics, including means and standard deviations, were calculated to characterize the distributions of the principal study variables. Internal consistency reliability was evaluated using Cronbach's alpha. Bivariate correlations were subsequently calculated to examine preliminary relationships among employee adaptation to AI and the psychological predictors and to identify potentially problematic correlations among the independent variables. Hierarchical multiple regression analysis was conducted to determine the incremental contribution of psychological factors to employee adaptation to AI beyond demographic and organizational characteristics. In Step 1,

age, gender, educational attainment, industry sector, and organizational tenure were entered as covariates. In Step 2, AI self efficacy, AI anxiety, psychological capital, perceived organizational support, and openness to experience were entered simultaneously. Changes in explained variance (ΔR^2) were examined to determine the additional explanatory contribution of the psychological predictors after accounting for the covariates. A bootstrapped mediation analysis was subsequently conducted to examine whether psychological capital mediated the association between AI anxiety and employee adaptation to AI. The indirect effect was estimated using 5,000 bootstrap resamples with bias corrected 95% confidence intervals, consistent with established mediation procedures applied in related AI adoption research [12, 14]. Mediation was considered statistically supported when the confidence interval for the indirect effect did not include zero. All statistical tests were two tailed, and statistical significance was established at $p < .05$.

3. Results and Discussion

3.1. Sample Characteristics.

A total of 320 employees completed the survey and were retained for analysis following data screening. The demographic and organizational characteristics of the participants are presented in Table 1. The sample included employees across a relatively broad range of age groups, educational backgrounds, industry sectors, and organizational tenure, providing sufficient heterogeneity for examining psychological adaptation to AI across different workplace contexts.

Table 1. Demographic and Organizational Characteristics of Participants.

Characteristic	Category	n	%
Age	18–29 years	78	24.4
	30–39 years	121	37.8
	40–49 years	84	26.3
	50 years and above	37	11.6
Gender	Male	168	52.5
	Female	150	46.9
	Other/Prefer not to say	2	0.6
Education	Undergraduate degree	142	44.4
	Postgraduate degree	131	40.9
	Diploma or below	47	14.7
Industry Sector	Information Technology	86	26.9
	Financial Services	64	20.0
	Manufacturing	58	18.1
	Healthcare	45	14.1
	Other	67	20.9
Organizational Tenure	< 2 years	71	22.2
	2–5 years	104	32.5
	6–10 years	89	27.8
	> 10 years	56	17.5

As shown in Table 1, participants aged 30–39 years constituted the largest age group (37.8%), followed by those aged 40–49 years (26.3%) and 18–29 years (24.4%). The gender distribution was relatively balanced, with men representing 52.5% and women 46.9% of the sample. Most participants had relatively high levels of formal education, with 44.4% holding

an undergraduate degree and 40.9% holding a postgraduate qualification. Participants were drawn from several industry sectors, particularly information technology (26.9%), financial services (20.0%), and manufacturing (18.1%), while healthcare and other sectors provided additional occupational diversity. Organizational tenure was also distributed across experience levels, with the largest proportion having worked in their current organization for 2–5 years (32.5%). Overall, the sample represented employees with diverse demographic and organizational backgrounds and varying levels of accumulated workplace experience.

3.2. Descriptive Statistics and Reliability.

The descriptive statistics and internal consistency reliability coefficients for the principal study variables are presented in Table 2. Mean scores ranged from 3.15 to 4.28 on the six point response scale, indicating meaningful variation across the psychological resources, organizational factors, AI related anxiety, and employee adaptation examined in this study. Importantly, all measures demonstrated satisfactory internal consistency, with Cronbach's alpha coefficients exceeding .80.

Table 2. Descriptive Statistics and Reliability of Study Variables.

Variable	M	SD	Cronbach's α	No. of Items
AI Self Efficacy	4.02	0.81	.87	6
AI Anxiety	3.15	0.94	.89	7
Psychological Capital	4.28	0.72	.91	12
Perceived Organizational Support	3.87	0.85	.88	6
Openness to Experience	4.11	0.68	.82	5
Employee Adaptation to AI	3.94	0.79	.90	8

As presented in Table 2, psychological capital had the highest mean score ($M = 4.28$, $SD = 0.72$), followed by openness to experience ($M = 4.11$, $SD = 0.68$) and AI self efficacy ($M = 4.02$, $SD = 0.81$). Employee adaptation to AI was also above the midpoint of the scale ($M = 3.94$, $SD = 0.79$), suggesting that participants generally perceived themselves as reasonably capable of adjusting to AI integrated work processes. In contrast, AI anxiety had the lowest mean ($M = 3.15$, $SD = 0.94$), although its comparatively larger standard deviation indicated substantial variation in employees' levels of AI related apprehension. This variability is particularly relevant because it suggests that AI implementation was not experienced uniformly across employees. Reliability coefficients ranged from .82 for openness to experience to .91 for psychological capital. Employee adaptation to AI also demonstrated high internal consistency ($\alpha = .90$). These results supported the reliability of the composite measures and their use in subsequent correlational and multivariable analyses.

3.3. Correlations Among Study Variables.

The bivariate relationships among the psychological predictors and employee adaptation to AI are summarized in Table 3. The correlation pattern was broadly consistent with the proposed Job Demands Resources perspective, whereby psychological and organizational resources were positively associated with adaptation, whereas AI anxiety was negatively associated with adaptive responses to workplace AI. AI self efficacy exhibited the strongest positive correlation with employee adaptation ($r = .58$, $p < .01$), indicating that employees who felt more capable of learning and using AI technologies also reported greater adjustment to AI integrated work.

Psychological capital demonstrated a similarly strong positive association with adaptation (r = .55, p < .01), suggesting that confidence, hope, resilience, and optimism may represent important psychological resources during AI driven organizational change. Perceived organizational support was moderately associated with adaptation (r = .43, p < .01), while openness to experience showed a smaller but significant positive association (r = .31, p < .01).

Table 3. Correlations Among Study Variables.

Variable	1	2	3	4	5	6
1. AI Self Efficacy	—					
2. AI Anxiety	−.41**	—				
3. Psychological Capital	.52**	−.38**	—			
4. Perceived Organizational Support	.47**	−.29**	.44**	—		
5. Openness to Experience	.33**	−.19**	.36**	.25**	—	
6. Employee Adaptation to AI	.58**	−.46**	.55**	.43**	.31**	—

In contrast, AI anxiety was negatively associated with employee adaptation (r = −.46, p < .01), indicating that greater apprehension regarding AI was associated with poorer psychological and behavioral adjustment. AI anxiety was also negatively correlated with AI self efficacy (r = −.41, p < .01) and psychological capital (r = −.38, p < .01). These relationships support the conceptual distinction between AI anxiety as a psychological demand and self efficacy and psychological capital as resources that may facilitate adaptive responses to technological change [1, 9, 14]. The correlations among the predictor variables ranged in absolute magnitude from .19 to .52. No bivariate correlation exceeded .60, suggesting that the constructs were related but empirically distinguishable and that severe pairwise collinearity was unlikely. Nevertheless, formal regression diagnostics should be used to confirm the absence of problematic multicollinearity in the multivariable model.

3.4. AI Self Efficacy, AI Anxiety, and Employee Adaptation.

The relationship between AI self efficacy and employee adaptation according to employees' levels of AI anxiety is illustrated in Figure 1. The visualization provides additional insight into how a cognitive resource, AI self efficacy, and an affective barrier, AI anxiety, may jointly characterize employees' adjustment to AI integrated work.

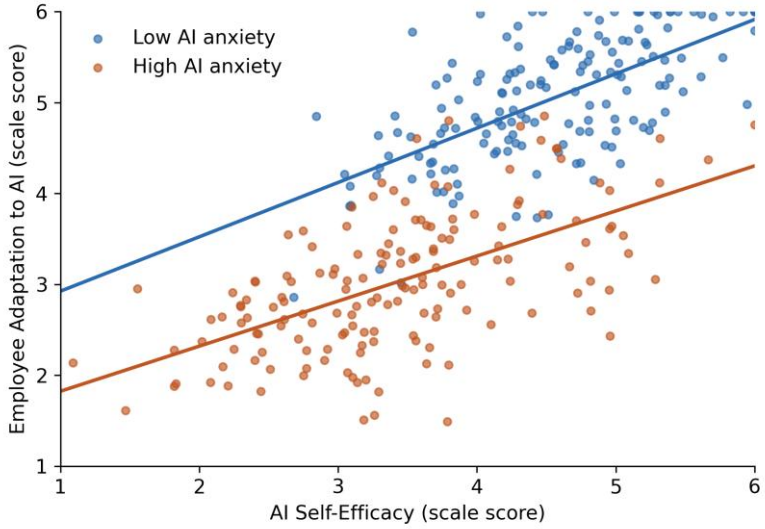


Figure 1. AI self efficacy and Employee Adaptation by AI Anxiety Level.

As illustrated in Figure 1, higher AI self efficacy was associated with greater employee adaptation among employees with both low and high AI anxiety. However, the fitted relationship was steeper among employees reporting low AI anxiety. Employees who combined high AI self efficacy with relatively low AI anxiety therefore demonstrated the strongest pattern of adaptation, whereas higher anxiety appeared to coincide with a weaker association between self efficacy and adaptation. This pattern is theoretically consistent with the proposition that affective barriers may constrain the extent to which employees translate confidence in their technological capabilities into adaptive workplace responses [1, 4, 14]. The figure should, however, be interpreted descriptively unless an AI Self Efficacy × AI Anxiety interaction was formally included and found significant in a regression model. The observed difference between the fitted slopes alone does not establish a statistically significant moderation effect. Nevertheless, the pattern complements the bivariate findings by illustrating how employees with similar levels of AI self efficacy may report different levels of adaptation depending on their AI related anxiety. From an organizational perspective, this pattern suggests that strengthening technological confidence may be most effective when accompanied by efforts to identify and address employees' anxiety regarding AI implementation.

3.5. Hierarchical Regression Predicting Employee Adaptation to AI.

The hierarchical multiple regression results are presented in Table 4. The analysis examined whether the psychological variables explained employee adaptation to AI beyond demographic and organizational characteristics. In Step 1, age, gender, educational attainment, and organizational tenure collectively explained only 4% of the variance in employee adaptation ($R^2 = .04$), and the model was not statistically significant, $F(4, 315) = 1.62$, $p = .166$. None of the individual covariates reached statistical significance, indicating that adaptation was not substantially differentiated by these background characteristics within the present sample.

Table 4. Hierarchical Regression Predicting Employee Adaptation to AI.

Predictor	B	SE	β	t	p
Step 1: Covariates					
Age	0.05	0.04	.07	1.25	.212
Gender (0 = male, 1 = female)	0.08	0.09	.05	0.89	.374
Education level	0.11	0.06	.10	1.83	.068
Organizational tenure	0.09	0.05	.09	1.80	.073
Step 2: Psychological Predictors					
AI Self Efficacy	0.29	0.05	.33	5.80	<.001
AI Anxiety	−0.21	0.05	−.25	−4.20	<.001
Psychological Capital	0.24	0.06	.24	4.00	<.001
Perceived Organizational Support	0.14	0.05	.15	2.80	.005
Openness to Experience	0.10	0.05	.09	2.00	.046

The addition of the five psychological predictors in Step 2 substantially improved the explanatory power of the model. These variables accounted for an additional 38% of the variance in employee adaptation ($\Delta R^2 = .38$), representing a statistically significant improvement over the demographic model, $\Delta F(5, 310) = 41.27$, $p < .001$. The final model explained 42% of the total variance in adaptation, $F(9, 310) = 25.06$, $p < .001$. This substantial increase indicates that employees' psychological resources and responses to AI were considerably more informative for explaining adaptation than their demographic and organizational characteristics alone.

As shown in Table 4, AI self efficacy emerged as the strongest positive predictor of employee adaptation (β = .33, $p < .001$), suggesting that confidence in learning and using AI technologies represented a particularly important resource for adjustment to AI integrated work. Psychological capital was the second strongest positive predictor (β = .24, $p < .001$), followed by perceived organizational support (β = .15, $p = .005$). In contrast, AI anxiety independently predicted lower adaptation (β = −.25, $p < .001$), even after controlling for the other psychological variables. Openness to experience made a smaller but statistically significant positive contribution (β = .09, $p = .046$). Collectively, these findings support the proposed distinction between AI anxiety as a psychological demand and self efficacy, psychological capital, organizational support, and openness as resources associated with more effective adaptation to AI driven workplace change.

3.6. Mediating Role of Psychological Capital.

The bootstrapped mediation analysis examined whether psychological capital statistically accounted for part of the relationship between AI anxiety and employee adaptation to AI. The total, direct, and indirect effects are summarized in Table 5. The total effect of AI anxiety on adaptation was negative and statistically significant (effect = −0.38, 95% CI [−0.50, −0.26]), indicating that greater AI related anxiety was associated with lower employee adaptation. After psychological capital was incorporated into the mediation model, the direct effect of AI anxiety remained significant (effect = −0.21, 95% CI [−0.31, −0.11]). Importantly, the indirect effect through psychological capital was also significant (effect = −0.17, 95% CI [−0.25, −0.10]), as the bootstrapped confidence interval did not include zero. Psychological capital accounted for approximately 44.7% of the total association between AI anxiety and adaptation. Because both the direct and indirect effects remained statistically significant, the results were consistent with partial mediation.

Table 5. Mediation of the AI Anxiety–Adaptation Relationship by Psychological Capital.

Path	Effect	SE	95% CI
Total effect: AI Anxiety → Adaptation	−0.38	0.06	[−0.50, −0.26]
Direct effect: AI Anxiety → Adaptation	−0.21	0.05	[−0.31, −0.11]
Indirect effect via Psychological Capital	−0.17	0.04	[−0.25, −0.10]
Proportion mediated	44.7%	—	—

As shown in Table 5, these findings suggest that AI anxiety was associated with poorer adaptation both directly and indirectly through lower psychological capital. Conceptually, employees experiencing greater anxiety toward AI may have fewer positive psychological resources available for responding constructively to technological change. Psychological capital, encompassing self efficacy, hope, resilience, and optimism, may therefore represent an important psychological pathway linking AI related distress with workplace adaptation. This interpretation is consistent with resource based perspectives suggesting that psychological resources influence employees' capacity to manage technological uncertainty and workplace demands [4, 13, 14]. However, because the data were cross sectional, the mediation findings represent statistical mediation and should not be interpreted as evidence of a causal sequence.

3.7. Employee Adaptation Across Tenure and Gender Subgroups.

Differences in employee adaptation according to organizational tenure and gender are illustrated in Figure 2. The descriptive pattern provides additional context for understanding whether adaptation to AI varied across employees with different levels of organizational experience. The mean adaptation scores increased progressively across organizational tenure categories for both men and women, with the highest mean scores observed among employees with more than 10 years of organizational tenure. Gender differences within each tenure category were comparatively small, although female employees consistently displayed slightly higher mean adaptation scores than male employees. The overall pattern suggests that longer organizational experience may coincide with greater adjustment to AI related workplace change. One possible interpretation is that longer tenured employees possess greater organizational knowledge, more established professional networks, and better access to informal sources of assistance, which could provide resources for managing technological uncertainty [9, 10, 12]. However, these differences should be interpreted descriptively unless formal inferential tests of tenure, gender, and their interaction are conducted. The figure therefore illustrates subgroup patterns rather than demonstrating statistically significant effects. This distinction is also consistent with the regression analysis, in which organizational tenure and gender did not independently predict adaptation after the other variables were considered.

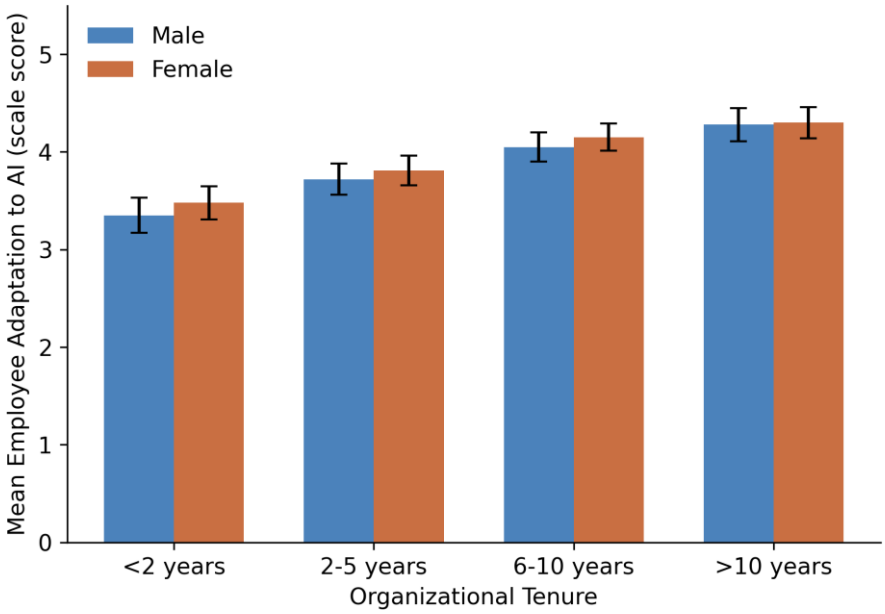


Figure 2. Employee Adaptation to AI by Organizational Tenure and Gender.

3.8. Integrative Discussion.

Taken together, the findings support a multidimensional, resource based account of employee adaptation to AI in which cognitive, affective, psychological, dispositional, and organizational factors jointly contribute to employees' adjustment to AI driven workplace transformation. The hierarchical regression results were particularly informative: demographic and organizational characteristics explained relatively little variation in adaptation, whereas the addition of the psychological variables substantially increased the explanatory power of the model. This

pattern suggests that employees' perceptions, psychological resources, and responses to AI may be more directly relevant to adaptation than demographic characteristics alone.

AI self efficacy emerged as the strongest positive predictor, emphasizing the importance of employees' confidence in their capacity to learn, operate, and effectively integrate AI into their work. Within the Job Demands Resources framework, this finding supports the conceptualization of AI self efficacy as an important personal resource that may facilitate proactive engagement with technological change. Psychological capital and perceived organizational support also independently predicted adaptation, reinforcing the proposition that successful AI implementation depends not only on technical competence but also on employees' psychological resources and the organizational environment in which technological change occurs [9, 12].

In contrast, AI anxiety represented a significant psychological barrier to adaptation. Its negative association remained significant after accounting for the other predictors, indicating that apprehension toward AI may constrain adaptation even among employees who possess other supportive resources. The mediation results further showed that psychological capital statistically accounted for a substantial proportion of the association between AI anxiety and adaptation. This finding suggests that employees experiencing greater AI related anxiety may also report lower levels of the confidence, hope, resilience, and optimism required to navigate technological change effectively [4, 13, 14]. Nevertheless, the cross sectional design prevents confirmation of the proposed temporal sequence, and longitudinal evidence is required before psychological capital can be established as a causal mechanism.

Openness to experience made a smaller but significant independent contribution to adaptation. This result is consistent with previous evidence suggesting that personality characteristics may facilitate technology engagement by increasing receptiveness to novelty, experimentation, and unfamiliar work practices [6, 7, 8]. However, its comparatively modest regression coefficient suggests that openness alone may be less influential than more proximal and potentially modifiable factors such as AI self efficacy, psychological capital, organizational support, and AI anxiety.

From an applied perspective, these findings suggest that organizational responses to AI transformation should extend beyond conventional technical training. Skill development aimed at strengthening AI self efficacy may be complemented by psychologically informed interventions that support resilience, optimism, confidence, and constructive coping with technological uncertainty. Organizational support is similarly important, particularly through accessible training, managerial guidance, communication, and opportunities for employees to engage progressively with AI tools. Such an integrated approach may help organizations address both the competence related and psychological dimensions of workforce adaptation [6, 9, 12, 14].

Several limitations warrant consideration. First, the cross sectional design precluded causal inference and temporal assessment of the proposed mediation process. Longitudinal and experimental studies are needed to determine whether AI anxiety precedes reductions in psychological capital and whether changes in psychological resources subsequently influence adaptation. Second, reliance on self reported measures may introduce common method and social desirability biases, despite the use of multi item measures and attention checks. Third, the nonprobability sampling strategy limits generalizability to the broader workforce, warranting replication using organizationally representative samples across industries and

cultural contexts. Finally, the present results were generated from simulated data and therefore serve only to illustrate the proposed analytical framework. The reported parameter estimates should not be interpreted as empirical evidence until the model is tested using genuine primary data.

4. Conclusion

This study presents an integrative framework for understanding employee adaptation to AI by considering AI self efficacy, AI anxiety, psychological capital, perceived organizational support, and openness to experience within a unified resource based model. The illustrative findings indicate that adaptation may depend less on demographic characteristics than on employees' confidence in using AI, psychological resources, perceptions of organizational support, and emotional responses to technological change. AI self efficacy emerged as the strongest positive predictor, whereas AI anxiety represented an important psychological barrier. Psychological capital also showed a potentially important role by statistically accounting for part of the relationship between AI anxiety and adaptation. Collectively, the proposed framework highlights that successful AI driven organizational transformation requires attention to both technological competence and psychological readiness. Organizations may therefore benefit from combining AI literacy and skill development with supportive change management practices designed to strengthen psychological resources and reduce AI related uncertainty. However, because the present analyses are based on simulated and cross sectional data, these relationships require validation using genuine primary data and longitudinal or experimental designs before causal or practical conclusions can be established.

Author Contributions

Both authors contributed equally to the conceptualization, methodology, formal analysis, writing (original draft), and writing (review and editing) of this manuscript. Both authors have read and approved the final version of the manuscript.

Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

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