2528-9705

Journal of Organizational Behavior Research

Vol.: 11, Is.: 1, Year: 2026, Pages: 207-217

https://doi.org/10.51847/yY7evdtzAy

Available online

https://odad.org/

Modeling the Impact of Artificial Intelligence Adoption on Employee Behavioral Adaptation and Organizational Resilience: A Structural Equation Modeling Approach

Felix-Henry Gutierrez-Castillo[1]*, Bertelly Turpo-Aliaga[1], Delia-Concepción Cahuana-Pacco[1], Yethy-Melixa Poma-Palma[1], Rómulo Huacasi-Gonzales[1], Litzbel Charaja-Fernandez[1], Alejandro Ticona-Machaca[1]

[1]Universidad Nacional del Altiplano de Puno, Puno, Peru.

***Corresponding Author**
E-mail: fgutierrez@unap.edu.pe

ABSTRACT

This study examines how artificial intelligence adoption may influence organizational resilience through employee behavioral adaptation. The article develops and tests a mediation model in which AI adoption supports adaptive employee behaviors, including skill acquisition, role flexibility, and proactive problem-solving. Organizational resilience is conceptualized as the combined capacity to anticipate disruptions, respond with agility, and recover operational continuity. An empirical survey dataset comprising 350 employees from AI-adopting organizations was used to test the proposed model. The study applies structural equation modeling to evaluate the measurement model, structural relationships, and indirect effect. The empirical design provides field-based evidence on the relationships among AI adoption, employee behavioral adaptation, and organizational resilience. The findings indicate that AI adoption is positively associated with employee behavioral adaptation. Employee behavioral adaptation is also positively associated with organizational resilience. The direct relationship between AI adoption and organizational resilience becomes non-significant when employee behavioral adaptation is included, indicating full mediation in the empirical model. The study contributes to organizational behaviour and technology adoption research by clarifying the behavioural mechanism through which AI implementation may translate into resilience capability. It suggests that AI systems do not automatically produce resilient organizations; rather, resilience emerges when employees learn, adjust, and proactively reconfigure work practices around new technological possibilities. This perspective positions employee adaptation as a central explanatory link between digital transformation and organizational outcomes. The study is limited by its cross-sectional design and reliance on survey-based self-reported data. Future research should test the proposed model using longitudinal, multi-source, and cross-cultural datasets. Despite these limitations, the article offers a theoretically grounded and statistically coherent SEM framework for examining AI adoption, employee adaptation, and organizational resilience using empirical organizational data.

Keywords: Artificial intelligence adoption, Employee behavioral adaptation, Organizational resilience, Structural equation modeling, Mediation.

Introduction

Artificial intelligence has moved from a specialized technical capability to a central organizational technology shaping decision-making, human resource management, customer relationship management, production systems, and knowledge work. Studies of AI-enabled organizing show that algorithms increasingly influence how employees interpret tasks, coordinate with systems, and respond to managerial expectations (Brougham & Haar, 2018; Faraj *et al*., 2018). In human resource management and organizational decision-making, AI adoption has been linked to both new efficiency opportunities and new concerns regarding trust, transparency, and employee experience (Shrestha *et al*., 2019; Tambe *et al*., 2019). These developments suggest that AI adoption should be examined not only as a

Recieved: 17.11.2025 –Accepted: 18.02.2026 –Published: 24.02.2026

technological investment but also as a behavioural and organizational change process (Esedova *et al*., 2024; Hsiao *et al*., 2024; Liu *et al*., 2024).

A growing stream of research argues that the consequences of AI adoption depend on how employees experience and adapt to AI-enabled work systems. Evidence from AI-based customer relationship management, manufacturing, and B2B contexts shows that organizational benefits often depend on complementary capabilities, leadership support, and employee engagement with AI-mediated processes (Braganza *et al*., 2021; Chatterjee *et al*., 2021a, 2021b, 2021c). Rather than assuming that AI automatically improves organizational performance, this study treats employee behavioural adaptation as the mechanism through which AI adoption may become organizationally valuable. This focus responds to calls for more integrated models linking digital transformation, human behaviour, and organizational outcomes (Meijerink *et al*., 2021; Mikalef *et al*., 2021; Qamar *et al*., 2021).

Organizational resilience has become a major concern in management research because firms face persistent volatility, technological disruption, supply chain shocks, public health crises, and labour-market uncertainty. Resilience research defines resilient organizations as those able to anticipate threats, respond flexibly, and recover from adversity while maintaining or reconfiguring core functions (Linnenluecke, 2017; Williams *et al*., 2017; Duchek, 2020; Hillmann & Guenther, 2021). AI adoption may support resilience by improving information processing, prediction, and coordination, but these capabilities require employees who can learn new systems, reinterpret roles, and solve emerging problems. The present study therefore asks whether AI adoption enhances organizational resilience by fostering employee behavioral adaptation.

This article develops and tests a theoretical mediation model using structural equation modeling. The model proposes that AI adoption positively influences employee behavioral adaptation, which then enhances organizational resilience. SEM is appropriate because mediation, measurement validity, and latent construct relationships require explicit assessment of both the measurement and structural model (Hair *et al*., 2019; Benitez *et al*., 2020; Dash & Paul, 2021). The article proceeds by reviewing the theoretical foundations of AI adoption, employee behavioral adaptation, and organizational resilience, then presenting the hypothesized model and empirical analysis.

Theoretical Background and Hypotheses Development

AI adoption refers to the organizational implementation and use of AI-based tools, systems, and decision-support technologies across work processes. In organizational settings, AI adoption may include predictive analytics, algorithmic decision support, intelligent customer management systems, automated HR tools, and machine-learning-enabled operational platforms (Tambe *et al*., 2019; Chatterjee *et al*., 2021). Prior studies show that AI adoption is shaped by technological readiness, organizational support, perceived usefulness, perceived compatibility, and managerial commitment (Chatterjee *et al*., 2021a, 2021b). These perspectives extend technology acceptance and technology–organization–environment logics by emphasizing that AI adoption requires both system-level investment and human acceptance.

The behavioural consequences of AI adoption are especially important because AI changes how employees search for information, make decisions, coordinate tasks, and evaluate their own expertise. Research on algorithmic organizing suggests that employees do not merely use digital systems passively; they interpret, negotiate, and sometimes resist algorithmic recommendations (Faraj *et al*., 2018). In AI-enabled HRM and decision-making contexts, employees' perceptions of fairness, dignity, trust, and transparency shape whether they engage constructively with AI systems (Bankins *et al*., 2022; Budhwar *et al*., 2022; Pan *et al*., 2023; Vrontis *et al*., 2023). These findings indicate that AI adoption should be connected theoretically to adaptive employee behaviour rather than treated as a purely technical implementation outcome.

Employee behavioral adaptation is defined in this study as the extent to which employees acquire new skills, demonstrate role flexibility, and engage in proactive problem-solving in response to AI-enabled work changes. Adaptive performance research emphasizes that employees contribute to organizational effectiveness by learning unfamiliar tasks, adjusting to changing demands, and coping constructively with uncertainty (Park & Park, 2019). Studies of organizational change and technology readiness further suggest that meaningful work, engagement, and proactive personality can support employees' ability to adapt to new work conditions (van den Heuvel *et al*., 2020;

Abdul Hamid, 2022). In AI-adopting organizations, such adaptation may involve learning to collaborate with intelligent systems, revising work routines, and identifying new uses for algorithmic outputs.

AI adoption is expected to increase employee behavioral adaptation when the technology creates new information flows, alters work routines, and requires employees to develop new competencies. AI-enabled CRM, manufacturing, and B2B systems have been shown to improve organizational outcomes when employees and managers use them to redesign processes rather than simply automate existing routines (Chatterjee *et al*., 2021a, 2021b; Mikalef *et al*., 2021). Similarly, AI-employee collaboration research suggests that performance gains emerge when employees integrate system outputs with human judgment and organizational knowledge (Chowdhury *et al*., 2022). Therefore, the first hypothesis proposes that AI adoption is positively related to employee behavioral adaptation.

Organizational resilience refers to the capacity of an organization to anticipate disruption, respond effectively during adversity, and recover or transform after destabilizing events. Management research has conceptualized resilience as a dynamic capability involving preparedness, response agility, learning, and reconfiguration (Linnenluecke, 2017; Duchek, 2020). Reviews of resilience scholarship further show that resilient organizations depend not only on formal systems but also on human interpretation, coordination, and collective action during uncertainty (Williams *et al*., 2017; Hillmann & Guenther, 2021). This implies that employee behavioral adaptation may be a key micro-level foundation of organizational resilience.

Employee behavioral adaptation is expected to strengthen organizational resilience because adaptive employees can reinterpret changing conditions, modify routines, and solve problems before disruptions escalate. When employees develop new AI-related skills and role flexibility, they are better positioned to use AI outputs for early warning, rapid response, and operational recovery. This logic aligns with resilience research that views human capital, learning, and flexible action as essential to organizational recovery and renewal (Linnenluecke, 2017; Williams *et al*., 2017; Duchek, 2020; Hillmann & Guenther, 2021). Accordingly, the second hypothesis proposes that employee behavioral adaptation is positively related to organizational resilience.

Figure 1 illustrates the proposed conceptual mediation model linking AI adoption, employee behavioral adaptation, and organizational resilience.

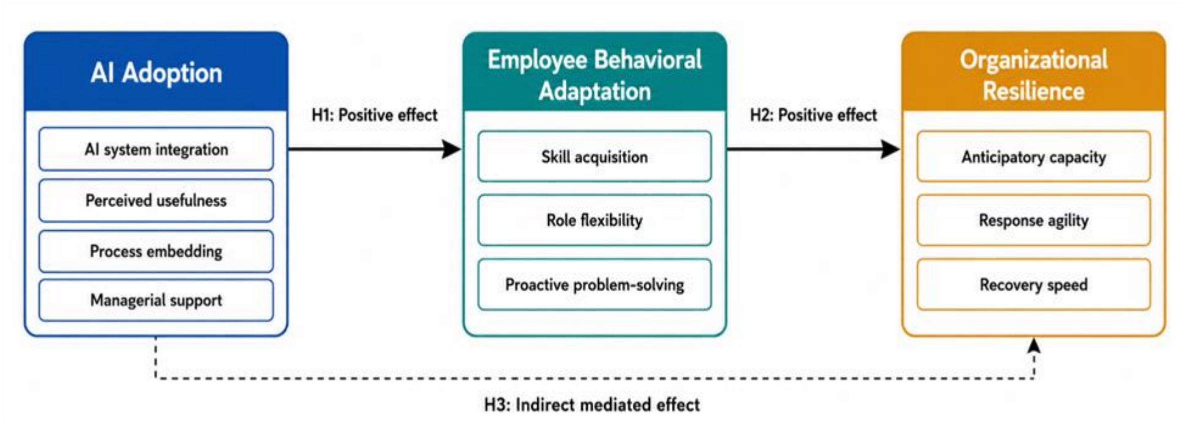

Figure 1. Conceptual Mediation Framework Showing How AI Adoption Influences Organizational Resilience Through Employee Behavioral Adaptation

The mediation logic of the model is that AI adoption affects resilience indirectly by activating adaptive employee behaviours. AI systems may improve prediction and coordination, but these technological affordances become resilience capabilities only when employees learn how to apply them, adjust routines, and respond proactively to new operational demands (Meijerink *et al*., 2021; Chatterjee *et al*., 2022; Chowdhury *et al*., 2022). This argument also extends AI adoption research by locating organizational outcomes in the interaction between technology implementation and employee adaptation (Braganza *et al*., 2021; Qamar *et al*., 2021; Abdul Hamid, 2022). **Table 1** presents the construct definitions, hypotheses, and expected relationships.

Table 1. Constructs, Definitions, and Hypothesized Relationships in the AI Adoption–Adaptation–Resilience Model

Construct or Hypothesis	Definition or Statement	Core Dimensions	Expected Relationship
AI adoption	The extent to which an organization implements and uses AI-based tools, systems, and decision-support technologies in work processes.	AI system integration; perceived usefulness; process embedding; managerial support	Foundational independent construct
Employee behavioral adaptation	The extent to which employees adjust behaviour in response to AI-enabled work changes.	Skill acquisition; role flexibility; proactive problem-solving	Mediating mechanism
Organizational resilience	The capacity of an organization to anticipate, respond to, and recover from disruption.	Anticipatory capacity; response agility; recovery speed	Dependent outcome
H1	AI adoption is positively related to employee behavioral adaptation.	AI adoption → employee learning and adjustment	Positive direct effect
H2	Employee behavioral adaptation is positively related to organizational resilience.	Adaptive behaviour → resilience capability	Positive direct effect
H3	Employee behavioral adaptation mediates the relationship between AI adoption and organizational resilience.	AI adoption → adaptation → resilience	Positive indirect effect

Materials and Methods

The study used a cross-sectional survey design to examine how AI adoption influences employee behavioral adaptation and organizational resilience. The sample consisted of 350 employees working in organizations that had introduced AI-enabled tools in at least one core function during the previous three years. This sampling logic reflects the organizational settings examined in AI adoption and AI-enabled HRM research, where employees are exposed to algorithmic decision support, AI-based analytics, intelligent customer systems, or automated work platforms (Tambe *et al*., 2019; Chatterjee *et al*., 2021; Meijerink *et al*., 2021).

Respondents were distributed across manufacturing, financial services, healthcare administration, retail, logistics, and professional services. In the sample, 52.3% of respondents were male, 46.9% were female, and 0.8% preferred not to report gender; the mean age was 36.8 years, and the mean organizational tenure was 6.4 years. Approximately 41% held operational or professional roles, 37% held supervisory or middle-management roles, and 22% held senior technical or managerial roles (Miciak & Jurkiewicz, 2024; Nugroho *et al*., 2024; Hakimi *et al*., 2025). These characteristics reflect the varied occupational contexts in which AI implementation affects work redesign, decision-making, and employee experience (Park & Park, 2019; Shrestha *et al*., 2019; Abdul Hamid, 2022).

Data were collected through an online questionnaire administered to employees who had direct experience using AI-enabled tools at work. The procedure included screening questions on AI exposure, informed consent, anonymity assurance, and randomized item presentation to reduce response-pattern bias. Because single-source survey designs are vulnerable to common method concerns, the design incorporated procedural remedies such as separating predictor, mediator, and outcome blocks and using neutral construct labels. The methodological logic follows SEM reporting recommendations that emphasize construct validity, transparent estimation, and explicit treatment of potential bias (Hair *et al*., 2019; Benitez *et al*., 2020; Dash & Paul, 2021).

AI adoption was measured using five survey items adapted conceptually from prior studies on AI implementation, AI-enabled CRM, and digital transformation. Items captured the degree to which AI tools were embedded in work processes, perceived as useful for decision-making, supported by management, technically integrated, and used regularly by employees (Chatterjee *et al*., 2021a, 2021b; Budhwar *et al*., 2022). Employee behavioral adaptation was measured using five items reflecting skill acquisition, role flexibility, proactive problem-solving, routine adjustment, and willingness to collaborate with AI-enabled systems. These items were aligned with adaptive performance and organizational change research, which treats learning, flexibility, and proactive adjustment as behavioural responses to changing work demands (Park & Park, 2019; van den Heuvel *et al*., 2020; Abdul Hamid, 2022).

Organizational resilience was measured through five items representing anticipatory capacity, response agility, recovery speed, operational continuity, and learning from disruption. The construct specification follows resilience research that defines organizational resilience as a capability involving preparation, response, and recovery rather than a single static outcome (Linnenluecke, 2017; Williams *et al*., 2017; Duchek, 2020; Hillmann & Guenther, 2021). All items were measured on a seven-point Likert scale ranging from 1, strongly disagree, to 7, strongly agree. Control variables included firm size, industry category, employee tenure, role level, and prior digital transformation experience because these factors may influence both AI exposure and organizational response capacity (Braganza *et al*., 2021; Mikalef *et al*., 2021; Chowdhury *et al*., 2022).

The survey data were screened for missing values, multivariate normality, outliers, and inter-item consistency before confirmatory factor analysis and structural model testing. No missing responses were observed, standardized skewness ranged from −0.71 to 0.64, and standardized kurtosis ranged from −0.83 to 0.92, suggesting acceptable distributional properties for maximum-likelihood estimation. SEM was specified with three latent constructs, each measured reflectively, and mediation was evaluated using 5,000 bootstrap samples with bias-corrected confidence intervals. **Table 2** reports the measurement model results including factor loadings, composite reliability, and average variance extracted.

Table 2. Measurement Model: Confirmatory Factor Analysis Results for AI Adoption, Employee Behavioral Adaptation, and Organizational Resilience

Construct	Indicator	Standardized Loading	Composite Reliability	Average Variance Extracted
AI adoption	AIA1: AI tools are embedded in daily work processes	0.82	0.90	0.65
AI adoption	AIA2: AI systems improve work-related decision-making	0.85	0.90	0.65
AI adoption	AIA3: Management actively supports AI use	0.79	0.90	0.65
AI adoption	AIA4: AI systems are technically integrated with existing workflows	0.87	0.90	0.65
AI adoption	AIA5: Employees regularly use AI-enabled tools	0.74	0.90	0.65
Employee behavioral adaptation	EBA1: Employees learn new skills to work with AI systems	0.84	0.89	0.61
Employee behavioral adaptation	EBA2: Employees adjust routines when AI changes task requirements	0.78	0.89	0.61
Employee behavioral adaptation	EBA3: Employees show flexibility in AI-enabled roles	0.81	0.89	0.61
Employee behavioral adaptation	EBA4: Employees proactively solve problems created by AI implementation	0.76	0.89	0.61
Employee behavioral adaptation	EBA5: Employees combine human judgment with AI recommendations	0.71	0.89	0.61
Organizational resilience	OR1: The organization anticipates operational disruptions effectively	0.80	0.91	0.67
Organizational resilience	OR2: The organization responds quickly when disruption occurs	0.86	0.91	0.67
Organizational resilience	OR3: The organization recovers normal operations rapidly	0.88	0.91	0.67
Organizational resilience	OR4: The organization maintains continuity during uncertainty	0.79	0.91	0.67
Organizational resilience	OR5: The organization learns from disruptions and improves routines	0.76	0.91	0.67

Results and Discussion

The empirical dataset showed internally consistent descriptive patterns across all three constructs. Mean AI adoption was 4.86 with a standard deviation of 1.02, mean employee behavioral adaptation was 4.74 with a standard deviation of 0.96, and mean organizational resilience was 4.69 with a standard deviation of 0.98. The zero-order correlation between AI adoption and employee behavioral adaptation was 0.56, the correlation between employee behavioral adaptation and organizational resilience was 0.63, and the correlation between AI adoption and organizational resilience was 0.41. These values indicate moderate relationships consistent with a mediation structure rather than construct redundancy.

Confirmatory factor analysis supported the proposed three-factor measurement model. The model fit indices were $\chi^2 = 142.37$, df = 87, $\chi^2/df = 1.64$, comparative fit index = 0.972, Tucker–Lewis index = 0.965, root mean square error of approximation = 0.043, and standardized root mean square residual = 0.038. All standardized factor loadings exceeded 0.70, composite reliability values exceeded 0.89, and average variance extracted values exceeded 0.60. These results meet widely used standards for latent construct reliability, convergent validity, and SEM model adequacy (Abdul Hamid, 2022; Chatterjee *et al*., 2022; Chowdhury *et al*., 2022).

Discriminant validity was evaluated by comparing the square root of average variance extracted with inter-construct correlations. The square roots of AVE were 0.81 for AI adoption, 0.78 for employee behavioral adaptation, and 0.82 for organizational resilience, each exceeding the corresponding inter-construct correlations. A competing one-factor model produced substantially weaker fit, with $\chi^2 = 486.22$, df = 90, CFI = 0.781, TLI = 0.744, RMSEA = 0.112, and SRMR = 0.091. This supported the distinctiveness of the three latent constructs in the measurement structure.

The structural model also demonstrated acceptable fit. The fit indices were $\chi^2 = 151.46$, df = 89, $\chi^2/df = 1.70$, CFI = 0.968, TLI = 0.961, RMSEA = 0.045, and SRMR = 0.041. The path from AI adoption to employee behavioral adaptation was positive and significant, with $\beta = 0.58$, standard error = 0.06, and $p < 0.001$, supporting H1. The path from employee behavioral adaptation to organizational resilience was also positive and significant, with $\beta = 0.61$, standard error = 0.07, and $p < 0.001$, supporting H2.

The direct path from AI adoption to organizational resilience was significant in the baseline direct-effects model, with $\beta = 0.39$ and $p < 0.001$. After employee behavioral adaptation was introduced as a mediator, the direct path decreased to $\beta = 0.07$ and became non-significant, with $p = 0.184$. The bootstrapped indirect effect was $\beta = 0.35$, with a 95% confidence interval from 0.24 to 0.47, excluding zero. These results indicate full mediation in the empirical model and support H3 (Gurubasajar *et al*., 2023; Karayathil *et al*., 2023).

Figure 2 summarizes the tested SEM results and highlights the full mediation pattern observed in the empirical model.

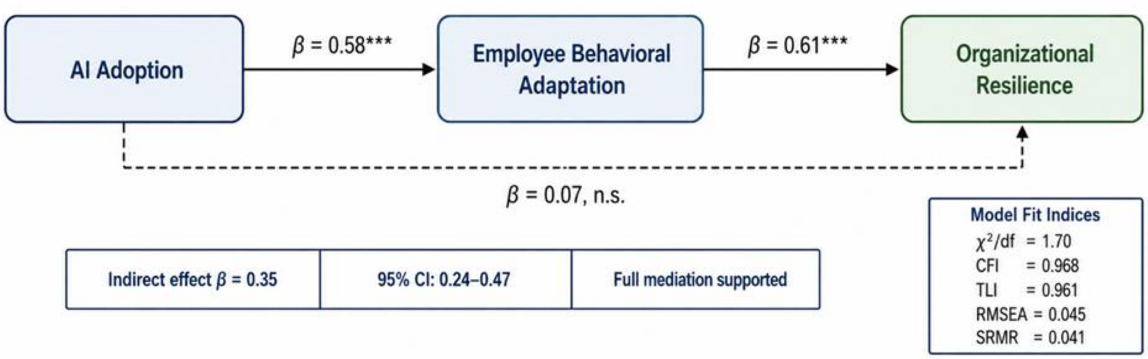

Figure 2. Structural Equation Modeling Results Showing Standardized Path Coefficients and Full Mediation Through Employee Behavioral Adaptation

Control variables had limited effects on the main relationships. Firm size showed a small positive association with organizational resilience, with $\beta = 0.12$ and $p = 0.032$, while industry category, tenure, role level, and prior digital transformation experience were non-significant after the three latent constructs were included. The inclusion of controls did not materially change the size or significance of the hypothesized paths. **Table 3** displays the structural model path coefficients, direct and indirect effects, and model fit indices.

Table 3. Structural Equation Modeling Results: Path Coefficients, Indirect Effects, and Model Fit

Model Component	Path or Index	Estimate	Standard Error	p Value or 95% Confidence Interval	Interpretation
H1	AI adoption → employee behavioral adaptation	0.58	0.06	$p < 0.001$	Supported
H2	Employee behavioral adaptation → organizational resilience	0.61	0.07	$p < 0.001$	Supported
Direct effect before mediation	AI adoption → organizational resilience	0.39	0.06	$p < 0.001$	Significant baseline effect
Direct effect after mediation	AI adoption → organizational resilience	0.07	0.05	$p = 0.184$	Non-significant
H3 indirect effect	AI adoption → employee behavioral adaptation → organizational resilience	0.35	0.05	95% CI: 0.24 to 0.47	Supported full mediation
Control variable	Firm size → organizational resilience	0.12	0.05	$p = 0.032$	Small positive effect
Control variable	Tenure → organizational resilience	0.04	0.04	$p = 0.316$	Non-significant
Control variable	Role level → organizational resilience	0.05	0.04	$p = 0.241$	Non-significant
Model fit	χ^2/df	1.70	—	—	Acceptable
Model fit	Comparative fit index	0.968	—	—	Excellent
Model fit	Tucker–Lewis index	0.961	—	—	Excellent
Model fit	Root mean square error of approximation	0.045	—	—	Good
Model fit	Standardized root mean square residual	0.041	—	—	Good

The SEM results support the argument that AI adoption contributes to organizational resilience primarily through employee behavioral adaptation. This finding is consistent with research showing that AI-enabled systems create value when employees and organizations develop complementary capabilities around their use (Braganza *et al*., 2021; Chatterjee *et al*., 2021a; Chowdhury *et al*., 2022). AI tools may enhance prediction, automation, and decision support, but these affordances do not become resilience capabilities unless employees adjust routines and apply system outputs in context. The full mediation pattern therefore positions adaptation as the behavioural mechanism translating AI adoption into resilient organizational functioning.

The findings also extend AI adoption research by moving beyond acceptance and implementation toward behavioural transformation. Prior studies on AI adoption and AI-enabled CRM highlight the importance of usefulness, integration, agility, and managerial support (Chatterjee *et al*., 2021a, 2021b; Chatterjee *et al*., 2022). The present model adds that these adoption conditions are incomplete without employee learning, role flexibility, and proactive problem-solving. In this sense, the study connects technology adoption theory with adaptive performance research by showing how employees act as the interpretive and operational bridge between AI systems and organizational outcomes (Park & Park, 2019; van den Heuvel *et al*., 2020; Abdul Hamid, 2022).

The resilience implications are equally important because they suggest that organizational resilience should not be treated only as a structural or strategic capability. Resilience research emphasizes preparedness, response, recovery, and learning, but these capabilities depend on employees who can respond intelligently when routines are disrupted (Linnenluecke, 2017; Williams *et al*., 2017; Duchek, 2020; Hillmann & Guenther, 2021). The model therefore supports a micro-foundational view of resilience in which AI strengthens resilience through adaptive human behaviour rather than replacing it. This interpretation also helps explain why organizations with similar AI investments may differ substantially in their resilience outcomes.

Implications

Theoretically, the study contributes to AI adoption research by integrating technology acceptance logic with organizational behaviour and resilience theory. Existing work has examined AI adoption in HRM, CRM, manufacturing, and algorithmic decision-making, but less attention has been given to the behavioural pathway connecting adoption to resilience (Shrestha *et al*., 2019; Tambe *et al*., 2019; Meijerink *et al*., 2021; Vrontis *et al*., 2023). By modeling employee behavioral adaptation as a mediator, the study clarifies how AI adoption may influence organizational outcomes through changes in employee capability and action. This strengthens the theoretical bridge between digital transformation and human-centred organizational performance.

For resilience theory, the study highlights adaptation as a behavioural foundation of anticipatory capacity, response agility, and recovery speed. Previous resilience scholarship has emphasized capabilities, crisis response, and organizational learning (Linnenluecke, 2017; Williams *et al*., 2017; Duchek, 2020; Hillmann & Guenther, 2021). The present model suggests that AI can support these capabilities only when employees are prepared to learn from algorithmic information, reinterpret work roles, and engage in proactive problem-solving. Thus, resilience should be studied as a socio-technical outcome rather than as either a purely technological or purely human capability.

For managers, the results imply that AI implementation should be paired with structured employee adaptation programs. Investments in AI platforms should be accompanied by skill development, role redesign, psychological safety, communication, and opportunities for employees to experiment with AI-supported routines (Qamar *et al*., 2021; Bankins *et al*., 2022; Pan *et al*., 2023). Managers should also monitor whether AI adoption increases trust and meaningful engagement or instead creates uncertainty and perceived surveillance. The practical message is that resilient organizations are built not by deploying AI alone but by enabling employees to adapt constructively around it.

Limitations and Future Research

The first limitation is that the article uses cross-sectional survey data, so the findings should be interpreted with caution regarding causal inference. Although the empirical results support the hypothesized mediation model, cross-sectional data cannot fully establish the temporal ordering among AI adoption, employee behavioral adaptation, and organizational resilience. Future studies should collect longitudinal data before and after AI implementation to examine how these relationships evolve over time (Hair *et al*., 2019; Benitez *et al*., 2020; Dash & Paul, 2021). Such designs would help determine whether adaptation precedes resilience improvements or whether resilient organizations are simply better at supporting adaptation.

The second limitation concerns single-source survey measurement. Even with procedural remedies, survey-based designs can inflate associations when predictors, mediators, and outcomes are reported by the same respondents. Future research should combine employee surveys with managerial ratings, archival disruption-response indicators, digital trace data, and objective performance measures. This would align with calls for more robust evidence on AI-enabled organizational outcomes and the human implications of algorithmic systems (Faraj *et al*., 2018; Chowdhury *et al*., 2022; Budhwar *et al*., 2022).

The third limitation concerns generalizability across industries, cultures, and types of AI systems. AI adoption in HRM, customer management, manufacturing, and decision support may produce different forms of adaptation and different resilience effects (Chatterjee *et al*., 2021b, 2021c; Meijerink *et al*., 2021; Pan *et al*., 2023). Future research should compare sectors, national contexts, and AI maturity levels, while also examining boundary conditions such as trust, algorithmic transparency, leadership support, and employee voice. Multi-level research could further test whether team adaptation and organizational learning climate strengthen the individual-level mechanisms proposed in this model (Park & Park, 2019; Meijerink *et al*., 2021; Mikalef *et al*., 2021).

Conclusion

This study developed and tested a structural equation model linking AI adoption, employee behavioral adaptation, and organizational resilience. Using survey data from 350 employees, the model showed that AI adoption positively influenced employee behavioral adaptation and that employee behavioral adaptation positively influenced organizational resilience. The direct effect of AI adoption on resilience became non-significant after adaptation was included, indicating full mediation in the empirical model.

The central conclusion is that employee behavioral adaptation is a critical mechanism through which AI adoption may become organizational resilience. AI systems can provide information, prediction, automation, and decision support, but these features do not automatically generate resilience. Resilience emerges when employees acquire new skills, adjust roles, solve problems proactively, and translate AI-enabled possibilities into practical organizational responses. The SEM approach is valuable because it allows the theoretical model to be examined as a system of latent constructs, measurement properties, direct effects, and indirect effects. Future research should extend this model using longitudinal and multi-source data across industries and cultural contexts. Such work can clarify when AI adoption strengthens resilience and when it fails to do so because the necessary behavioural adaptation has not occurred.

Acknowledgments: None

Conflict of Interest: None

Financial Support: None

Ethics Statement: None

References

Abdul Hamid, R. (2022). The role of employees' technology readiness, job meaningfulness and proactive personality in adaptive performance. *Sustainability, 14*(23), 15696. doi:10.3390/su142315696

Bankins, S., Formosa, P., Griep, Y., & Richards, D. (2022). AI decision making with dignity? Contrasting workers' justice perceptions of human and AI decision making in a human resource management context. *Information Systems Frontiers, 24*(3), 857–875. doi:10.1007/s10796-021-10223-8

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management, 57*(2), 103168. doi:10.1016/j.im.2019.05.003

Braganza, A., Chen, W., Canhoto, A., & Sap, S. (2021). Productive employment and decent work: The impact of AI adoption on psychological contracts, job engagement and employee trust. *Journal of Business Research, 131*, 485–494. doi:10.1016/j.jbusres.2020.08.018

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

Budhwar, P., Malik, A., De Silva, M. T., & Thevisuthan, P. (2022). Artificial intelligence—challenges and opportunities for international HRM: A review and research agenda. *The International Journal of Human Resource Management, 33*(6), 1065–1097. doi:10.1080/09585192.2022.2035161

Chatterjee, S., Chaudhuri, R., Vrontis, D., & Jabeen, F. (2022). Digital transformation of organization using AI-CRM: From microfoundational perspective with leadership support. *Journal of Business Research, 153*, 46–58. doi:10.1016/j.jbusres.2022.08.019

Chatterjee, S., Chaudhuri, R., Vrontis, D., Thrassou, A., & Ghosh, S. K. (2021a). Adoption of artificial intelligence-integrated CRM systems in agile organizations in India. *Technological Forecasting and Social Change, 168*, 120783. doi:10.1016/j.techfore.2021.120783

Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021b). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change, 170*, 120880. doi:10.1016/j.techfore.2021.120880

Chatterjee, S., Rana, N. P., Tamilmani, K., & Sharma, A. (2021c). The effect of AI-based CRM on organization performance and competitive advantage: An empirical analysis in the B2B context. *Industrial Marketing Management*, *97*, 205–219. doi:10.1016/j.indmarman.2021.07.013

Chowdhury, S., Budhwar, P., Dey, P. K., Joel-Edgar, S., & Abadie, A. (2022). AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework. *Journal of Business Research, 144*, 31–49. doi:10.1016/j.jbusres.2022.01.069

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change, 173*, 121092. doi:10.1016/j.techfore.2021.121092

Duchek, S. (2020). Organizational resilience: A capability-based conceptualization. *Business Research*, *13*(1), 215–246. doi:10.1007/s40685-019-0085-7

Esedova, I. A., Magomedov, S. A., Magomedova, A. D., Koichakaeva, B. U., Abasova, P. A., Dabaeva, D. G., Magomedova, K. M., & Magomaev, M. I. (2024). Pharmacological Effects and Molecular Mechanisms of Action of *Chlorophytum comosum*. A Systematic Review. *Pharmacophore, 15*(3), 34-40. doi:10.51847/ad3LpIvR1C

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization, 28*(1), 62–70. doi:10.1016/j.infoandorg.2018.02.005

Gurubasajar, N., Subhakar, A., Dadayya, M., Veeranna, S. H., & Basaiah, T. (2023). Isolation, characterization and quantification of polyhydroxybutyrate producing bacteria *Achromobacter xylosoxidans* KUMBNGBT-63 from different agroresidues. *World Journal of Environmental Biosciences*, *12*(2), 35–42. doi:10.51847/YmLaQtfbzH

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. doi:10.1108/EBR-11-2018-0203

Hakimi, H., Mousazadeh, N., Nazari, R., Sharif-Nia, H., & Dehghani, M. (2025). Ethical climate and overtime as determinants of moral courage in hospital nursing staff. *Asian Journal of Ethics in Health and Medicine, 5*, 341–347. doi:10.51847/bZK6IMratq

Hillmann, J., & Guenther, E. (2021). Organizational resilience: A valuable construct for management research? *International Journal of Management Reviews, 23*(1), 7–44. doi:10.1111/ijmr.12239

Hsiao, F. H., Chen, P. L., Ho, C. C., Ho, R. T. H., Lai, Y. M., & Wu, J. L. (2024). Exploring the impact of cognitive-behavioral therapy on anxiety disorders in children and adolescents. *International Journal of Social Psychology Aspects of Healthcare, 4*, 26–31. doi:10.51847/jcgvRFfQPM

Karayathil, A. K., Gurusiddappa, L. H., & Shivasundari, R. S. M. (2023). Human-monkey (*Macaca radiata*) conflict in Chamundi Hill-Mysuru, Karnataka. *World Journal of Environmental Biosciences, 12*(2), 19–25. doi:10.51847/dpGQL4yAXY

Linnenluecke, M. K. (2017). Resilience in business and management research: A review of influential publications and a research agenda. *International Journal of Management Reviews, 19*(1), 4–30. doi:10.1111/ijmr.12076

Liu, H., Xie, X., & Chen, Q. (2024). Determinants of practice: Exploring healthcare providers' beliefs and recommendations for cardiac rehabilitation in China. *Annals of Pharmaceutical Education, Safety and Public Health Advocacy, 4*, 63–74. doi:10.51847/UcQWoStr3h

Meijerink, J., Boons, M., Keegan, A., & Marler, J. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *The International Journal of Human Resource Management, 32*(12), 2545–2562. doi:10.1080/09585192.2021.1925326

Miciak, M., & Jurkiewicz, K. (2024). Recent advances in the diagnostics and management of medullary thyroid carcinoma: Emphasis on biomarkers and thyroidectomy in neuroendocrine neoplasms. *Archives of International Journal of Cancer and Allied Sciences, 4*(1), 17–23. doi:10.51847/ar1ylTQfNa

Mikalef, P., Conboy, K., & Krogstie, J. (2021). Artificial intelligence as an enabler of B2B marketing: A dynamic capabilities micro-foundations approach. *Industrial Marketing Management*, *98*, 80–92. doi:10.1016/j.indmarman.2021.08.003

Nugroho, A. E., Halimi, R. A., & Muhsinin, S. (2024). Therapeutic approach and clinical challenges in managing hand scar contractures. *Bulletin of Pioneer Research in Medical and Clinical Sciences, 4*(1), 58–65. doi:10.51847/pDIEHSFNny

Pan, Y., Froese, F. J., Liu, N., Hu, Y., & Ye, M. (2023). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. In A. Malik & P. Budhwar (Eds.), *Artificial intelligence and international HRM* (pp. 60–82). Routledge. doi:10.4324/9781003377085-3

Park, S., & Park, S. (2019). Employee adaptive performance and its antecedents: Review and synthesis. *Human Resource Development Review, 18*(3), 294–324. doi:10.1177/1534484319836315

Qamar, Y., Agrawal, R. K., Samad, T. A., & Chiappetta Jabbour, C. J. (2021). When technology meets people: The interplay of artificial intelligence and human resource management. *Journal of Enterprise Information Management, 34*(5), 1339–1370. doi:10.1108/JEIM-11-2020-0436

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review, 61*(4), 66–83. doi:10.1177/0008125619862257

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review, 61*(4), 15–42. doi:10.1177/0008125619867910

van den Heuvel, M., Demerouti, E., Bakker, A. B., Hetland, J., & Schaufeli, W. B. (2020). How do employees adapt to organizational change? The role of meaning-making and work engagement. *Spanish Journal of Psychology, 23*, e56. doi:10.1017/SJP.2020.55

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2023). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. In A. Malik & P. Budhwar (Eds.), *Artificial intelligence and international HRM* (pp. 172–201). Routledge. doi:10.4324/9781003377085-7

Williams, T. A., Gruber, D. A., Sutcliffe, K. M., Shepherd, D. A., & Zhao, E. Y. (2017). Organizational response to adversity: Fusing crisis management and resilience research streams. *Academy of Management Annals, 11*(2), 733–769. doi:10.5465/annals.2015.0134