

AI ADOPTION IN HRM, ORGANIZATIONAL LEARNING CAPABILITY, TECHNOLOGICAL TRUST, AND ORGANIZATIONAL EFFECTIVENESS

Rahul Kumar Choudhary, Institute of Management Studies, Banaras Hindu University, India

Abhijeet Singh, Institute of Management Studies, Banaras Hindu University, Varanasi, India

Monika Singh, Institute of Management Studies, Banaras Hindu University, India

ABSTRACT

The growing infusion of artificial intelligence (AI) into Human Resource Management (HRM) promises to reshape the way organizations recruit, develop, and manage employees. However, evidence about whether AI truly enhances organizational effectiveness remains inconclusive. This paper develops and empirically examines a model in which AI adoption in HRM affects organizational effectiveness both directly and indirectly through two mediators: organizational learning capability and technological trust. Grounded in socio-technical systems theory, the knowledge-based view, and the technology acceptance literature, we argue that AI improves outcomes when organizations possess the capacity to learn from new data-driven insights and when stakeholders trust the systems that generate them. Using a two-wave survey of medium and large firms, we test the model with Partial Least Squares Structural Equation Modeling (PLS-SEM) and complement it with fuzzy-set Qualitative Comparative Analysis (fsQCA) to explore equifinal pathways. Results show that organizational learning capability and technological trust are both significant mediators, suggesting that AI is not a plug-in solution but rather a socio-technical transformation. The study contributes to theory by integrating technological and organizational perspectives, and to practice by highlighting that managers must invest not only in AI systems but also in trust-building and learning infrastructures to realize their benefits.

Keywords: AI Adoption, HRM, Organizational Learning Capability, Technological Trust, Organizational Effectiveness.

INTRODUCTION

Artificial intelligence is rapidly moving from hype to reality in the management of human resources. Organizations today deploy AI to screen résumés, conduct video interviews, personalize employee learning, and forecast workforce attrition Jarrahi, (2018). The appeal is obvious: AI promises greater efficiency, accuracy, and fairness than traditional HR practices. Yet, organizational experiences with AI are uneven. Some firms report significant gains in productivity and talent outcomes, while others encounter resistance, ethical controversies, and negligible performance improvements Argyris, (1996). This divergence raises a critical research question: under what conditions does AI adoption in HRM lead to higher organizational effectiveness?

This study addresses that question by investigating two mediating factors that link AI adoption in HRM to organizational effectiveness: organizational learning capability (OLC) and technological trust (TT). AI produces insights and recommendations, but unless an

organization can learn from them collectively, their value remains untapped. At the same time, if employees and managers distrust AI-based systems—viewing them as unreliable, opaque, or unfair—its recommendations may be ignored or resisted. We argue that OLC and TT are therefore essential socio-technical mechanisms through which AI adoption in HRM can translate into improved organizational effectiveness. Colquitt, et al., (2007)

LITERATURE REVIEW

Socio-technical systems theory posits that technological and social subsystems must be jointly optimized for an organization to perform effectively. Adopting AI without attention to learning processes or trust structures risks failure, as the technology cannot function in isolation. The knowledge-based view further highlights that competitive advantage flows from the creation, integration, and application of knowledge. AI-enabled HR practices generate new forms of knowledge about people and processes, but only organizations with strong learning routines can internalize this knowledge and translate it into improved effectiveness McElheran et al., (2024).

Organizational learning capability has long been identified as a strategic resource that supports innovation, adaptation, and resilience. Research shows that organizations with high OLC are more adept at converting information into actionable insights, and at diffusing these insights across units. AI adoption can strengthen OLC by creating feedback loops and cross-functional knowledge exchanges, but equally, without OLC the potential of AI may remain underutilized Jerez-Gomez et al., (2005).

Technological trust represents the belief that a system is reliable, competent, and aligned with organizational values. In the HR domain, where fairness and ethics are particularly salient, trust in AI systems is critical. If employees fear that AI is biased or that decisions are made without accountability, the legitimacy of AI-driven HR processes collapses Bodó, (2021). Conversely, when trust is present, employees are more likely to accept AI-assisted recommendations, thereby enabling the organization to realize efficiency and fairness gains.

Taken together, these perspectives suggest a mediated relationship: AI adoption in HRM enhances organizational learning capability and technological trust, which in turn strengthen organizational effectiveness Venkatesh et al., (2012).

Hypotheses

Based on the preceding discussion, we hypothesize the following relationships:

- H₁: AI adoption in HRM positively influences organizational learning capability.*
- H₂: AI adoption in HRM positively influences technological trust.*
- H₃: Organizational learning capability positively influences organizational effectiveness.*
- H₄: Technological trust positively influences organizational effectiveness.*
- H_{5a}: Organizational learning capability mediates the relationship between AI adoption and organizational effectiveness.*
- H_{5b}: Technological trust mediates the relationship between AI adoption and organizational effectiveness.*

METHODOLOGY

Research Design and Sample

To test the model, we designed a two-wave, multi-source survey of organizations with at least 100 employees, drawn from both service and manufacturing industries. In Wave 1, HR managers provided information about AI adoption in HRM. In Wave 2, conducted six

weeks later, line managers and employees assessed organizational learning capability, technological trust, and organizational effectiveness. This design reduced common-method variance and ensured that the data reflected multiple perspectives within each firm.

A total of 218 organizations participated, representing diverse industries such as information technology, finance, healthcare, and logistics. On average, organizations had 1,250 employees and had been experimenting with AI in HRM for 2.8 years.

Measures

All constructs were measured with validated Likert-type scales (1 = strongly disagree, 7 = strongly agree). AI adoption in HRM was captured through items on AI use in recruitment, performance evaluation, training, and workforce planning. Organizational learning capability was measured through indicators of knowledge acquisition, dissemination, and interpretation Nonaka & Takeuchi (2007). Technological trust included items capturing perceived reliability, competence, and fairness of AI systems. Organizational effectiveness was measured with items on productivity, service quality, and employee engagement. Control variables included firm size, industry, and HR digital maturity.

Data Analysis

We employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4 to test the hypothesized paths. Reliability and validity checks were conducted before estimating the structural model. Mediation tests were carried out using bootstrapping procedures Ragin, (2008). To complement the net-effect analysis, we also applied fuzzy-set Qualitative Comparative Analysis (fsQCA) to identify alternative configurations of conditions leading to high organizational effectiveness.

RESULTS

Measurement Model

Composite reliability values ranged from 0.87 to 0.94, exceeding the recommended threshold of 0.70. Average Variance Extracted (AVE) values ranged between 0.56 and 0.72, indicating convergent validity. Discriminant validity was established through the HTMT criterion, with all values below 0.85. Variance inflation factors (VIFs) were well below 3.3, suggesting no multicollinearity concerns.

Structural Model

Bootstrapping results (5,000 resamples) showed that AI adoption in HRM had a significant positive effect on both organizational learning capability ($\beta = 0.41$, $p < .001$) and technological trust ($\beta = 0.36$, $p < .001$). In turn, organizational learning capability ($\beta = 0.33$, $p < .01$) and technological trust ($\beta = 0.29$, $p < .01$) both positively influenced organizational effectiveness. The direct path from AI adoption to organizational effectiveness remained significant ($\beta = 0.21$, $p < .05$), suggesting partial mediation.

The R^2 for organizational effectiveness was 0.52, indicating that the model explained more than half of the variance in the outcome variable. Predictive relevance (Q^2) values were positive, confirming the model's predictive validity.

Table 1 PLS-SEM RESULTS					
Hypothesis	Path	β (Coefficient)	t-value	p-value	Result

H1	AI-HRM → OLC	0.41	6.12	< .001	Supported
H2	AI-HRM → TT	0.36	5.47	< .001	Supported
H3	OLC → OE	0.33	3.85	< .01	Supported
H4	TT → OE	0.29	3.42	< .01	Supported
H5a	AI-HRM → OLC → OE	0.14	3.21	< .01	Supported
H5b	AI-HRM → TT → OE	0.11	2.87	< .01	Supported
Direct Effect	AI-HRM → OE	0.21	2.15	< .05	Supported

Note: OLC = Organizational Learning Capability; TT = Technological Trust; OE = Organizational Effectiveness

Discussion

The findings of this study provide compelling evidence that AI adoption in HRM contributes to organizational effectiveness, but the relationship is far from straightforward. The direct effect of AI on effectiveness is significant, but relatively modest. The real gains materialize when organizations possess high learning capability and when employees trust the AI systems being used. Both organizational learning capability and technological trust emerged as significant mediators, confirming that AI adoption is most effective when accompanied by supportive organizational and psychological infrastructures.

These results align with socio-technical systems theory by underscoring the need for joint optimization of technical and social systems. From the perspective of the knowledge-based view, the findings suggest that AI enhances effectiveness not simply by providing more data, but by enabling organizations to generate and internalize knowledge. For practitioners, the message is clear: AI investments in HRM must be complemented with initiatives that build organizational learning routines and foster trust through transparency, explainability, and ethical safeguards.

CONCLUSION

This study contributes to the literature on AI in organizations by offering an integrated socio-technical explanation of how AI adoption in HRM affects organizational effectiveness. By demonstrating the mediating roles of organizational learning capability and technological trust, it shows that AI adoption is not a plug-and-play solution but a transformation that requires cultural and relational adjustments. Future research should examine moderating conditions such as industry turbulence, national culture, or regulatory contexts. For managers, the findings suggest that the road to AI-enabled effectiveness is paved not only with algorithms but also with trust and learning.

REFERENCES

- Argyris, C. (1996). Organizational learning II. Theory, method, and practice.
- Bodó, B. (2021). Mediated trust: A theoretical framework to address the trustworthiness of technological trust mediators. *New Media & Society*, 23(9), 2668-2690.
- Colquitt, J. A., Scott, B. A., & LePine, J. A. (2007). Trust, trustworthiness, and trust propensity: a meta-analytic test of their unique relationships with risk taking and job performance. *Journal of applied psychology*, 92(4), 909.
- Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business horizons*, 61(4), 577-586.
- Jerez-Gomez, P., Céspedes-Lorente, J., & Valle-Cabrera, R. (2005). Organizational learning capability: a proposal of measurement. *Journal of business research*, 58(6), 715-725.
- McElheran, K., Li, J. F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L., & Zolas, N. (2024). AI adoption in America: Who, what, and where. *Journal of Economics & Management Strategy*, 33(2), 375-415.
- Nonaka, I., & Takeuchi, H. (2007). The knowledge-creating company. *Harvard business review*, 85(7/8), 162.
- Ragin, C. C. (2009). *Redesigning social inquiry: Fuzzy sets and beyond*. University of Chicago press.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178.

Received: 16-Sep-2025, Manuscript No. AMSJ-25-16262; **Editor assigned:** 17-Sep-2025, PreQC No. AMSJ-25-16262(PQ); **Reviewed:** 11-Oct-2025, QC No. AMSJ-25-16262; **Revised:** 28-Oct-2025, Manuscript No. AMSJ-25-16262(R); **Published:** 02-Nov-2025