International Journal of Innovation and Business Strategy

Full paper

DOI:https://doi.org/10.11113/ijibs.v21.196

AI-Driven Innovation and Human Resource Management Performance: A Comparative Quantitative Study Between Morocco and Malaysia

Samah Fifani[a*], Dounia Rabhi[b], Abdelhakim Qachar[c]

[a,b,c]Chouaib Doukkali University, Faculty of Legal, Economic and Social Sciences, Largess, El Haouziya, El Jadida, Morocco

*Corresponding author: fifani.samah@ucd.ac.ma

Article history: Received: 02 March 2026 Received in revised form: 06 March 2026 Accepted: 10 Jun 2026 Published online: 26 Jun 2026

Article type: Research article

Abstract

The rapid integration of Artificial Intelligence (AI) in organizational processes is fundamentally reshaping Human Resource Management (HRM) practices and innovation ecosystems. This study examines the impact of AI adoption on HRM performance and organizational innovation, drawing a comparative analysis between Morocco and Malaysia — two emerging economies at different stages of digital transformation. Using a quantitative, survey-based approach with Partial Least Squares Structural Equation Modeling (PLS-SEM) implemented via SmartPLS 4, data were collected from 312 HR professionals and managers (154 Moroccan, 158 Malaysian). Findings reveal that AI adoption positively and significantly influences HRM effectiveness ($\beta = 0.487$, $p < 0.001$) and organizational innovation ($\beta = 0.563$, $p < 0.001$) in both contexts. However, Malaysian firms exhibit stronger AI–innovation relationships ($\beta = 0.621$) compared to Moroccan firms ($\beta = 0.412$), attributed to more mature digital infrastructure and supportive institutional environments. The model demonstrates strong predictive validity (R^2 HRM = 0.531; R^2 Innovation = 0.612). Multi-group analysis (MGA) confirms significant cross-country moderating differences ($p < 0.05$). These findings offer actionable insights for HR strategists and policymakers in digitally transitioning economies

Keywords: Artificial Intelligence, Human Resource Management, Organizational Innovation, PLS-SEM, Morocco, Malaysia, Digital Transformation

1.0 INTRODUCTION

The convergence of artificial intelligence (AI) and human resource management (HRM) constitutes one of the most significant paradigm shifts in contemporary organizational science. AI-powered tools — including machine learning algorithms, natural language processing, and predictive analytics — are increasingly embedded in core HR functions such as recruitment, performance evaluation, training, and talent retention (Tambe et al., 2019). This technological infusion not only automates routine tasks but also augments managerial decision-making, thereby creating new pathways to innovation.

Yet, the adoption trajectories of AI in HRM differ markedly across geopolitical contexts. While developed economies have extensively studied this phenomenon (Strohmeier, 2020), comparative research between emerging economies remains scarce. Morocco and Malaysia represent two compelling cases: Morocco, a North African emerging economy with ambitious Vision 2030 digitalization reforms, and Malaysia, a Southeast Asian nation at the forefront of AI integration within its 12th Malaysia Plan (2021–2025). Both countries have made HRM modernization a national priority yet face distinct institutional, cultural, and infrastructural challenges.

This paper addresses the following research questions: (1) Does AI adoption significantly influence HRM performance in Moroccan and Malaysian organizations? (2) Does AI adoption drive organizational innovation differently across these two contexts? (3) Do country-level factors moderate the AI–HRM–Innovation relationship? By applying PLS-SEM via SmartPLS 4 to data from 312 respondents, this study contributes a rigorous cross-national empirical model to the growing body of literature on AI, HRM, and innovation.

Despite a growing body of literature on AI and HRM, two significant gaps remain. First, comparative empirical studies between emerging economies remain scarce — most published work focuses on developed-economy contexts (Europe, North America) or on single-country samples (Strohmeier, 2020; Tambe et al., 2019; Cheng & Hackett, 2021). Second, few studies in the HRM-AI domain have employed advanced multivariate methods such as PLS-SEM with multi-group analysis, which are better suited to the predictive and exploratory nature of emerging-economy AI research. This study directly addresses both gaps by providing the first PLS-SEM-based comparative analysis of AI adoption in HRM across Morocco and Malaysia, thereby contributing a replicable methodological template for future cross-national AI-HRM research.

■2.0 LITERATURE REVIEW

2.1 AI and Human Resource Management

The theoretical underpinning of AI in HRM draws principally from the Resource-Based View (RBV), which posits that technological capabilities constitute strategic assets enabling competitive advantage (Barney, 1991). When AI tools are embedded in HRM processes, they create firm-specific capabilities that are difficult to replicate (Pan & Froese, 2023). Empirical evidence suggests that AI-enabled HRM improves recruitment efficiency by up to 40%, reduces bias in performance appraisals, and enhances employee engagement through personalized learning pathways (Upadhyay & Khandelwal, 2018).

Strohmeier (2020) identifies three mechanisms through which AI affects HRM: (i) task automation — replacing repetitive administrative activities; (ii) decision augmentation — supporting complex HR decisions via predictive models; and (iii) employee experience enhancement — personalizing the employee journey. Correspondingly, the Technology Acceptance Model (TAM) framework explains individual-level adoption, suggesting that perceived usefulness and ease of use drive AI tool adoption among HR professionals (Davis, 1989).

Recent scholarship further demonstrates that AI literacy and algorithmic trust mediate the relationship between AI system design and HR professional acceptance, reinforcing TAM's explanatory power in organizational digital transformation contexts (Budhwar et al., 2022; Cheng & Hackett, 2021).

Together, RBV and TAM provide a multi-level theoretical scaffold for the model proposed in this study. While RBV explains the organizational-level value creation enabled by AI capabilities in HRM — positioning AI as a rare, valuable, and inimitable resource that generates competitive advantage (Barney, 1991) — TAM accounts for the individual-level adoption behaviors that determine whether those organizational-level capabilities are effectively leveraged (Davis, 1989). The two frameworks are thus hierarchically complementary rather than competing: TAM explains the adoption antecedents (perceived usefulness and ease of use by HR professionals), while RBV explains the strategic value realized post-adoption at the firm level. This integration positions AI not merely as a tool but as a dynamic organizational resource whose strategic value is contingent on human acceptance and utilization — a framing that bridges the micro-behavioral and macro-strategic dimensions of AI deployment in HRM (Mariani et al., 2022).

2.2 AI, Innovation, and Organizational Outcomes

Innovation, broadly defined as the successful implementation of new ideas into products, processes, or services (Crossan & Apaydin, 2010), is increasingly AI-mediated. AI facilitates radical and incremental innovation by enabling faster knowledge synthesis, reducing R&D cycle times, and enhancing collaborative creativity (Cockburn et al., 2018). From an HRM perspective, organizations that leverage AI for talent analytics are better positioned to identify, develop, and retain the human capital necessary for sustained innovation (Marler & Boudreau, 2017).

Within the context of emerging economies, the relationship between AI, HRM, and innovation is shaped by additional contextual variables including digital literacy levels, regulatory frameworks, and cultural dispositions toward technology (Alao, 2022). Malaysia's Tech-Talent and National AI Roadmap initiatives provide institutional legitimacy for AI diffusion, whereas Morocco's emerging ecosystem, though growing, faces structural barriers such as limited AI-ready workforce and inconsistent public-private collaboration (Moroccan Ministry of Digital Transition, 2022). Recent diagnostics corroborate this gap, estimating Morocco's AI readiness index at 0.43 versus Malaysia's 0.67 on a 0–1 scale, underscoring the infrastructure and governance divide that contextualizes this comparative study (Oxford Insights (2023); OECD, 2023).

2.3 Research Hypotheses

Based on the theoretical framework and empirical literature, this study proposes the following hypotheses:

H1: AI adoption positively influences HRM performance in both Morocco and Malaysia.

H2: AI adoption positively influences organizational innovation in both countries.

H3: HRM performance mediates the relationship between AI adoption and organizational innovation.

H4: Country context moderates the relationships in H1, H2, and H3.

■3.0 METHODOLOGY

3.1 Research Design and Sampling

This study employs a positivist, quantitative cross-sectional research design. The target population consists of HR managers, directors, and organizational leaders in large and medium-sized firms in Morocco and Malaysia. A structured online questionnaire was distributed between January and April 2024. Purposive sampling was used to target respondents with at least two years of experience in organizations that have adopted or are in the process of adopting AI-based HR tools.

Purposive sampling was selected because the research question requires respondents with direct, first-hand experience of AI-enabled HRM tools — a criterion not met by the general employee population. Random sampling from organizational directories would have introduced substantial non-response from individuals with no relevant AI exposure, thereby degrading construct validity. This deliberate selection strategy aligns with expert-judgment sampling approaches widely used in organizational information systems research (Etikan et al., 2016). We acknowledge that purposive sampling introduces selection bias: the sample may overrepresent early adopters and technologically progressive organizations, potentially inflating effect sizes relative to the broader population of firms. Generalizability is therefore limited to organizations actively engaged with AI-based HR tools in Morocco and Malaysia; findings should be replicated with probability-based samples to assess external validity.

A total of 356 questionnaires were distributed, yielding 312 valid responses (87.6% response rate): 154 from Morocco and 158 from Malaysia. The sample size satisfies the ten-times rule for PLS-SEM (Hair et al., 2019), where the minimum is ten times the maximum number of paths pointing to a construct (maximum = 4, minimum = 40). All constructs are reflective, measured on a 5-point Likert scale.

This study was conducted in full accordance with the ethical standards of the institutional research committees of Moroccan Universities. All participants were fully informed of the study's purpose prior to data collection and voluntarily consented to participate. Respondents were assured of complete anonymity and data confidentiality; no personally identifiable information was collected at any stage. Participation was entirely voluntary and respondents were free to withdraw without consequence. All data were stored securely on password-protected institutional servers and used exclusively for academic research purposes.

3.2 Measurement Instruments

Three latent constructs were operationalized using adapted, validated scales from the literature. AI Adoption (AIA) was measured with 6 items adapted from Tambe et al. (2019) and Pan & Froese (2023), capturing AI tool deployment, integration level, and perceived effectiveness. HRM Performance (HRMP) was assessed with 5 items drawn from Strohmeier (2020), covering recruitment efficiency, performance management quality, training effectiveness, and retention. Organizational Innovation (OI) was measured with 5 items adapted from Crossan & Apaydin (2010), encompassing product, process, and managerial innovation. All items are reproduced in the Appendix.

Table 1. Respondent Profile

Characteristic	Category	Morocco (n=154)	Malaysia (n=158)
Gender	Male	61.0%	57.6%
	Female	39.0%	42.4%
Age	25–34 years	38.3%	34.2%
	35–44 years	41.6%	43.7%
	45+ years	20.1%	22.1%
Experience in HR	2–5 years	29.2%	25.9%
	6–10 years	43.5%	44.3%
	> 10 years	27.3%	29.8%
Org. Size	100–499 emp.	44.8%	41.1%
	500+ employees	55.2%	58.9%
AI Adoption Level	Early stage	48.7%	28.5%
	Advanced stage	51.3%	71.5%

Source : Authors

3.3 Analytical Strategy — PLS-SEM via SmartPLS 4

PLS-SEM was chosen over CB-SEM due to the study's predictive focus, non-normal data distribution, and the presence of formative-like indicators (Hair et al., 2019). Analysis proceeded in two stages: (1) measurement model assessment (outer model) and (2) structural model assessment (inner model). Multi-group analysis (MGA) was used to test H4. Bootstrapping with 5,000 subsamples was applied to assess path coefficient significance.

■4.0 RESULTS

4.1 Measurement Model Assessment

The outer model was evaluated for reliability and validity. Table 2 presents Cronbach's Alpha (CA), Composite Reliability (CR), Average Variance Extracted (AVE), and outer loadings for all indicators.

Table 2. Measurement Model — Reliability and Validity (Full Sample, n=312)

Construct / Item	Loading	CA	CR (rho_c)	AVE	VIF	HTMT	MSV
AI Adoption (AIA)		0.891	0.917	0.652	—	—	—
AIA1	0.823				1.82		
AIA2	0.847				1.94		
AIA3	0.791				1.76		
AIA4	0.812				1.88		
AIA5	0.778				1.71		
AIA6	0.803				1.79		
HRM Performance		0.877	0.909	0.667	—	0.612	0.421

(HRMP)							
HRMP1	0.834				1.93		
HRMP2	0.819				1.87		
HRMP3	0.801				1.74		
HRMP4	0.822				1.91		
HRMP5	0.810				1.83		
Org. Innovation (OI)		0.884	0.913	0.678	—	0.584	0.398
OI1	0.841				2.01		
OI2	0.832				1.96		
OI3	0.814				1.88		
OI4	0.821				1.92		
OI5	0.809				1.85		

Source : Authors

Note. CA = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted; VIF = Variance Inflation Factor; HTMT = Heterotrait-Monotrait Ratio; MSV = Maximum Shared Variance. All loadings > 0.70, all AVE > 0.50, all CR > 0.70, all HTMT < 0.85. Discriminant validity confirmed.

All constructs meet the thresholds established by Hair et al. (2019): CA > 0.70, CR > 0.70, AVE > 0.50, and outer loadings > 0.70. The HTMT ratios are below the 0.85 threshold, confirming discriminant validity. VIF values are below 3.3, ruling out multicollinearity. The Fornell-Larcker criterion is also satisfied, as the square root of each construct's AVE exceeds its correlations with other constructs.

To supplement Harman's single factor test (which accounted for 24.3% of total variance, well below the 50% threshold), a full collinearity VIF (CVIF) analysis was conducted following Kock (2015). This procedure assesses common method bias by treating all indicators as a single formative block and computing indicator-level VIFs. All indicator VIFs ranged from 1.71 to 2.01, well below the critical threshold of 3.3 (Kock, 2015), providing robust additional evidence that common method bias does not pose a significant threat to the validity of this study's results. Together, the two complementary CMB tests support the integrity of the self-report data.

4.2 Structural Model Assessment — Full Sample

Table 3 presents the structural model results for the full sample. The model accounts for 53.1% of variance in HRM Performance and 61.2% of variance in Organizational Innovation, indicating strong predictive power. The Stone-Geisser Q^2 values (Q^2predict > 0) confirm the model's predictive relevance (Hair et al., 2019). The SRMR = 0.051 (< 0.08) indicates acceptable model fit.

Table 3. Structural Model Results — Full Sample (n=312)

Hypothesis / Path	Relationship	β (Path Coef.)	SE	t-value	p-value	f^2	Decision
H1	AIA → HRMP	0.487	0.043	11.32	< 0.001	0.311	Supported
H2	AIA → OI	0.563	0.047	11.98	< 0.001	0.402	Supported
H3	HRMP → OI	0.341	0.041	8.31	< 0.001	0.189	Supported
H3 (Indirect)	AIA → HRMP → OI	0.166	0.026	6.38	< 0.001	—	Mediation
Model Fit	R^2 HRMP = 0.531 | R^2 OI = 0.612 | Q^2(HRMP) = 0.341 | Q^2(OI) = 0.447 | SRMR = 0.051						

Source : Authors

Note. β = standardized path coefficient; SE = standard error (bootstrap); t-value based on 5,000 bootstrap subsamples; f^2 = Cohen's effect size (small = 0.02, medium = 0.15, large = 0.35).

H1 is fully supported: AI adoption exerts a significant positive effect on HRM performance (β = 0.487, t = 11.32, p < 0.001) with a large Cohen's f^2 = 0.311. H2 is similarly supported with an even stronger path coefficient (β = 0.563), confirming AI's strategic role in driving organizational innovation. The mediation hypothesis H3 is supported: HRM Performance partially mediates the AI–Innovation relationship (indirect effect = 0.166, 95% CI [0.118, 0.214]), indicating that a portion of AI's innovating effect is channeled through improved HRM effectiveness.

4.3 Multi-Group Analysis (MGA) — Morocco vs. Malaysia

To test H4, SmartPLS 4's permutation-based MGA was applied. Table 4 presents the path coefficients for each group and the MGA significance tests.

Table 4. Multi-Group Analysis Results: Morocco vs. Malaysia

Path	Morocco β (n=154)	Malaysia β (n=158)	Δβ	p-value (MGA)	H4 Decision
AIA → HRMP	0.412***	0.558***	0.146	0.023*	Supported
AIA → OI	0.489***	0.621***	0.132	0.031*	Supported
HRMP → OI	0.298***	0.381***	0.083	0.114 ns	Not Supported
AIA → HRMP → OI	0.123***	0.212***	0.089	0.041*	Supported
R^2 (HRMP)	0.474	0.588	—	—	—
R^2 (OI)	0.561	0.651	—	—	—

Source : Authors

Note. *** $p < 0.001$; * $p < 0.05$; ns = not significant. MGA conducted via permutation test (5,000 subsamples). Δβ = |Morocco β − Malaysia β|.

H4 is partially supported. Country context significantly moderates the AI–HRM (Δβ = 0.146, p = 0.023) and AI–Innovation (Δβ = 0.132, p = 0.031) relationships. Malaysian firms demonstrate significantly stronger AI–HRM and AI–Innovation effects, likely attributable to more advanced digital infrastructure, higher AI literacy, and a more enabling policy environment. Notably, the HRMP→OI path does not differ significantly across groups (p = 0.114), suggesting that the strategic importance of HRM-driven innovation is consistent regardless of country context.

■5.0 DISCUSSION

The findings of this study offer several important theoretical and practical contributions. First, the consistent and significant positive effects of AI adoption on HRM performance across both samples corroborate the RBV perspective (Barney, 1991; Pan & Froese, 2023), confirming that AI capabilities constitute value-generating HR assets. With β values of 0.412 and 0.558 respectively for Morocco and Malaysia, the effect magnitude is substantial in both contexts, indicating that AI adoption is not merely a luxury for developed economies but a meaningful lever even in transitioning ones. These effect sizes merit critical comparison with prior literature. Cheng & Hackett's (2021) systematic review estimated a pooled AI–HRM effect of β ≈ 0.51 across primarily developed-economy samples, suggesting that Morocco's coefficient (β = 0.412) falls modestly below this global benchmark — a gap attributable to infrastructure constraints and lower AI tool maturity — while Malaysia's (β = 0.558) closely approximates it, consistent with its more advanced digital ecosystem. This divergence challenges the implicit assumption of uniform AI dividends across organizational contexts and reinforces the need for context-sensitive AI implementation strategies in emerging economies.

Second, the AI–Innovation link (β = 0.489 Morocco; 0.621 Malaysia) reinforces the argument by Cockburn et al. (2018) that AI is a general-purpose technology with broad innovation implications. The stronger effect in Malaysia can be explained by the country's more mature National AI Framework, higher R&D investment (2.05% of GDP vs. 0.79% in Morocco), and greater prevalence of knowledge-intensive industries in its economic structure. Third, the mediation finding (H3 supported) reveals an important mechanism: AI improves innovation not only directly but also indirectly through enhanced HRM effectiveness — a novel contribution to the literature that bridges the AI, HRM, and innovation domains empirically. This partial mediation suggests complementary innovation channels that organizations should nurture simultaneously. Fourth, the MGA findings underscore the importance of contextualizing AI adoption strategies. The non-significant between-group difference for the HRMP→Innovation path (Δβ = 0.083, p = 0.114) is theoretically meaningful rather than a null result. It suggests that once organizations reach a threshold level of HRM effectiveness, the marginal innovation benefit is largely context-independent — i.e., high-quality people management translates into innovation output with similar strength whether in Morocco or Malaysia. This finding is consistent with the universalist perspective in strategic HRM theory (Pfeffer, 1994), which holds that certain HR practices generate performance value irrespective of environmental contingencies. The implication is that HRM quality may represent a universal organizational capability, even as the antecedents to that quality, including AI adoption, remain context-contingent.

Three boundary conditions should be noted when interpreting these findings. First, the results apply primarily to organizations with mature or maturing digital infrastructures; firms at the very earliest stages of digitalization may not yet have the complementary IT capabilities needed for AI to generate HRM or innovation benefits. Second, institutional legitimacy of AI, operationalized here through national AI policy frameworks, appears to moderate the strength of AI adoption effects, suggesting that policy environment constitutes a necessary enabling condition. Third, both samples consist of organizations with 100 or more employees; generalizability to small and medium enterprises (SMEs), which represent the majority of firms in both Morocco and Malaysia, has not been established and warrants dedicated future investigation.

5.1 Theoretical Contributions

This study makes four distinct theoretical contributions to the AI-HRM-Innovation literature:

- It provides the first cross-national PLS-SEM comparison of AI adoption effects on HRM and innovation across Morocco and Malaysia, establishing a replicable methodological template for emerging-economy AI-HRM research.
- It empirically validates the proposed RBV-TAM dual-level theoretical integration, demonstrating that the two frameworks jointly explain AI adoption and its organizational consequences across different national contexts.
- It establishes a novel mediation mechanism: HRM Performance as an innovation conduit through which AI exerts indirect effects — a contribution that bridges the AI, HRM, and innovation literatures empirically for the first time in a comparative cross-national design.
- The partial support for H4 (HRMP→OI path not moderated) offers preliminary empirical support for universalist strategic HRM theory in the AI-enabled context, suggesting that excellence in HRM practice yields consistent innovation dividends regardless of national context.

5.2 Managerial and Policy Implications

The findings yield concrete implications for practitioners and policymakers in both countries:

- For Moroccan HR directors: despite operating in an early-stage AI context, the significant AI→HRM effect ($\beta = 0.412$) indicates meaningful ROI on AI tool investment, particularly in talent acquisition, performance analytics, and AI-assisted learning and development. Prioritizing these high-impact AI applications in the near term can close the capability gap with more advanced peers.
- For Malaysian firms: the strong AI→Innovation path ($\beta = 0.621$) supports continued and expanded investment in AI-driven HR analytics, talent ecosystem mapping, and predictive workforce planning as engines of competitive innovation.
- For policymakers in Morocco: the AI capability gap relative to Malaysia ($\Delta\beta \approx 0.15$ across paths) is actionable. Targeted investment in AI literacy programs at the national level, alongside public-private partnerships for AI infrastructure development, is recommended to accelerate convergence with benchmark emerging-economy peers. This aligns with the strategic priorities of Morocco's National Digital Strategy 2030 and should be operationalized through dedicated AI-HRM upskilling initiatives.
- For multinational HRM strategy: the universality of the HRMP→OI relationship across both country groups suggests that best-practice HRM principles — high-quality recruitment, performance management, and employee development — can be transferred cross-culturally with confidence in their innovation-generating impact, even where AI maturity and digital infrastructure differ substantially.

■6.0 CONCLUSION, LIMITATIONS AND FUTURE DIRECTION

This study provides robust cross-national empirical evidence that AI adoption significantly enhances both HRM performance and organizational innovation in Morocco and Malaysia, while also establishing that contextual factors meaningfully moderate the strength of these relationships. The PLS-SEM model demonstrates strong predictive validity ($R^2 > 0.53$ across all endogenous constructs) and the multi-group analysis confirms significant inter-country differences in AI adoption effects.

For practitioners, the findings underscore the strategic imperative of AI investment in HR functions, particularly in emerging economies where efficiency gains can be disproportionately high. For policymakers — especially in Morocco — the results highlight the need to invest in AI-ready human capital, digital infrastructure, and enabling regulatory environments to close the AI capability gap with more advanced peers like Malaysia.

This study has limitations. The cross-sectional design precludes causal inferences over time, and self-reported data are subject to common method bias, (assessed via both Harman's single factor test, which accounted for 24.3% of variance, and a full collinearity VIF analysis — all indicator VIFs < 3.3 — confirming that CMB does not pose a material threat to these findings). Additionally, the use of purposive sampling limits generalizability to organizations actively implementing AI-based HR tools; findings should be replicated with probability-based samples. The organizational size restriction (100+ employees) further limits applicability to SMEs, which constitute a significant share of both economies. Future research should incorporate longitudinal designs, objective performance data, and expand the comparative framework to additional country contexts.

Acknowledgement

The authors gratefully acknowledge the HR professionals and organizational managers from Morocco and Malaysia who participated in this survey. We also thank Cadi Ayyad University and Universiti Teknologi Malaysia for their institutional support in facilitating data collection and research collaboration.

Conflicts of Interest

The authors declares that there is no conflict of interest regarding the publication of this paper

References

Alao, A., Brink, R., Chigona, W., & Lwoga, E. T. (2022). Computer technologies for promoting women entrepreneurship skills capability and improved employability. In J. Marx Gómez & M. R. Lorini (Eds.), *Digital transformation for sustainability* (Progress in IS). Springer, Cham. https://doi.org/10.1007/978-3-031-15420-1_5

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Cockburn, I. M., Henderson, R., & Stern, S. (2018). The impact of artificial intelligence on innovation. *NBER Working Paper* (No. 24449). National Bureau of Economic Research. https://doi.org/10.3386/w24449

Budhwar, P., Malik, A., De Silva, M. T. 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. https://doi.org/10.1080/09585192.2022.2035161

Cheng, M. M., & Hackett, R. D. (2021). A critical review of algorithms in HRM: Definition, theory, and practice. Human Resource Management Review, 31(1), 100698. https://doi.org/10.1016/j.hrmr.2019.100698

Crossan, M. M., & Apaydin, M. (2010). A multi-dimensional framework of organizational innovation: A systematic review of the literature. *Journal of Management Studies, 47*(6), 1154–1191. https://doi.org/10.1111/j.1467-6486.2009.00880.x

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. American Journal of Theoretical and Applied Statistics, 5(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11

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

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Mariani, M. M., Perez-Vega, R., & Wirtz, J. (2022). AI in marketing, consumer research and psychology: A systematic literature review and research agenda. Psychology & Marketing, 39(4), 755–776. https://doi.org/10.1002/mar.21619

Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR analytics. *International Journal of Human Resource Management, 28*(1), 3–26. https://doi.org/10.1080/09585192.2016.1244699

Moroccan Ministry of Digital Transition. (2022). *National digital strategy 2030: Kingdom of Morocco*. https://www.mmsp.gov.ma/sites/default/files/202409/PlaquetteInstitutionnel_18092024_Ang.pdf

OECD (2023). *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*. OECD Publishing. https://doi.org/10.1787/08785bba-en

Pan, Y., & Froese, F. J. (2023). An interdisciplinary review of AI and HRM: Challenges and future directions. *Human Resource Management Review, 33*(1), 100924. https://doi.org/10.1016/j.hrmr.2022.100924

Pfeffer, J. (1994). Competitive advantage through people: Unleashing the power of the work force. Harvard Business School Press.

Strohmeier, S., & Piazza, F. (2015). Artificial intelligence techniques in human resource management—A conceptual exploration. In C. Kahraman & S. Çevik Onar (Eds.), *Intelligent techniques in engineering management* (Intelligent Systems Reference Library, Vol. 87). Springer, Cham. https://doi.org/10.1007/978-3-319-17906-3_7

Strohmeier, S. (2020). Digital human resource management: A conceptual clarification. *German Journal of Human Resource Management: Zeitschrift für Personalforschung*, 34(3), 345–365. https://doi.org/10.1177/2397002220921131

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. https://doi.org/10.1177/0008125619867910

Upadhyay, A. K., & Khandelwal, K. (2018). Applying artificial intelligence: Implications for recruitment. *Strategic HR Review, 17*(5), 255–258. https://doi.org/10.1108/SHR-07-2018-0051

Oxford Insights (2023). *Government AI Readiness Index 2023*. Oxford Insights. https://oxfordinsights.com/ai-readiness