Original Article
ISSN (Online): 2582-7472

ShodhKosh: Journal of Visual and Performing Arts
July-December 2024 5(2), 711–720

BEYOND AUTOMATION: AI AS A STRATEGIC PARTNER IN TALENT DEVELOPMENT FOR KPO/BPO/ITES SECTOR

Khadija Mohasin [1], Dr. Pravin Mane [2]

[1] Research Scholar, Bharati Vidyapeeth (Deemed to be University), Institute of Management and Entrepreneurship Development Pune, India
[2] Assistant Professor, Bharati Vidyapeeth (Deemed to be University), Institute of Management and Entrepreneurship Development Pune, India

ABSTRACT

As artificial intelligence (AI) technologies mature, their role in talent development is undergoing a profound transformation—moving beyond operational automation toward strategic partnership in workforce growth. This study explores the evolving integration of AI-enabled solutions in KPO, BPO, and ITES sectors, with a particular emphasis on how organizations are leveraging these technologies to redefine human resource management (HRM) practices, widely regarded as a burgeoning outsourcing and technology hub, offers a fertile landscape for analyzing the complex dynamics between AI adoption, organizational preparedness, and stakeholder engagement. This research investigates the nuanced shift from AI as a task-oriented facilitator to AI as a co-creator of personalized learning and performance pathways. Through exploratory fieldwork comprising surveys, semi-structured interviews, and secondary data analysis, the study captures first-hand insights from HR managers, line managers, and operational staff across various outsourcing enterprises. Central to the analysis are three intersecting dimensions: (1) the perception of HR and line managers regarding AI's strategic value in talent development; (2) organizational readiness for adopting AI-driven platforms in learning, performance management, and succession planning; and (3) ethical and psychological implications tied to AI-led interventions. These include concerns around algorithmic bias, transparency, employee trust, and emotional responses to automated evaluation mechanisms. The research foregrounds the perspectives of multi-HR managers and line managers to provide a balanced understanding of how human-AI collaboration is influencing the cultural, procedural, and strategic aspects of Talent development. Findings reveal a growing inclination among organizations to adopt hyper-personalized development frameworks, replacing traditional and one-size-fits-all training models. AI platforms are increasingly used to deliver real-time feedback, simulate contextual problem-solving scenarios, and provide just-in-time learning nudges aligned with evolving job roles. It proposes that strategic use of AI in talent development anchored in transparent governance and HR and Line Manager trust can help outsourcing firms in build resilient, future-ready workforces. The findings aim to inform not only policy-makers and organizational leaders but also researchers seeking to advance interdisciplinary frameworks for AI-Talent development integration.

Keywords: Automation, Strategic, Development, KPO/BPO/ITES Sector

DOI
10.29121/shodhkosh.v5.i2.2024.6455

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

1. INTRODUCTION

This study seeks to explore how AI technologies are transitioning from being tools of automation to becoming strategic enablers of talent development within KPO, BPO, and ITES sectors. By investigating the perceptions of HR managers and line managers, the research delves into the complex interplay between technological readiness, organizational culture, and ethical considerations. The rapid adoption of AI-driven platforms such as predictive learning analytics, natural language processing, and conversational agents is prompting a re-evaluation of traditional performance Leadership development and future role alignment frameworks.

The incorporation of AI in talent development offers several transformative possibilities. Intelligent platforms now have the capacity to deliver personalized learning content, simulate job-specific problem-solving tasks, and provide real-time feedback all tailored to individual employee trajectories and evolving job roles. Moreover, the deployment of conversational AI in hybrid work settings supports micro-interventions and virtual coaching, fostering decentralized and self-directed learning. These developments signal a fundamental shift toward dynamic, responsive talent ecosystems in which human capability is continuously shaped through iterative engagement with intelligent systems. However, the promise of AI-driven talent development also presents substantial challenges. Ethical concerns related to algorithmic bias, transparency, and data privacy intersect with psychological dimensions such as employee trust, emotional responses to machine-led evaluations, and readiness to embrace digitally mediated growth. As organizations navigate this terrain, the role of HR leaders is becoming increasingly complex. Not only must they manage the operational implications of AI adoption, but they must also serve as change agents who can interpret, communicate, and shape the human consequences of technological transformation.

In this context, the study positions AI not merely as a functional tool but as a strategic partner one capable of co-authoring talent narratives, aligning workforce capabilities with business objectives, and reimagining HRM through an ethical and human-centric lens. By analyzing multi-stakeholder insights and real-world implementations, the research contributes to an emerging discourse on how organizations can move beyond automation and embrace AI as an integral part of their strategic development agenda.

2. REVIEW OF LITERATURE

The integration of artificial intelligence (AI) into human resource management (HRM), particularly in performance management systems (PMS) and talent development, has emerged as a transformative force in contemporary organizational practices. Multiple scholars have explored this convergence, illustrating AI's capacity to enhance efficiency, personalization, and strategic decision-making. Bhatt and Muduli (2022) emphasize that AI innovations like natural language processing and machine learning have revolutionized learning and development (L&D) processes by enabling personalized module delivery, learner recognition, and real-time feedback. These findings underscore AI's contribution to scalable and cost-effective learning, marking a significant departure from traditional training models.

Tusquellas, Palau, and Santiago (2024) present a systemic literature review suggesting that the future of talent management will be defined by the adoption of AI-powered applications that streamline recruitment, performance monitoring, and employee development. Their synthesis advocates for investments in AI skills enhancement and continuous learning programs, indicating a shift from resource-centric management to intelligence-driven practices. Similarly, Rezaei and Beyerlein (2018) offer foundational insights into talent development, identifying managerial barriers and highlighting the importance of formal interventions. However, they also note the conceptual ambiguity between talent development (TD) and human resource development (HRD), inviting further clarification in the literature—a gap your work directly addresses.

Fernandes (2023) critically examine AI's potential for organizational talent identification and performance prediction, calling for the creation of advanced models that empower managers through nuanced analytics. Their emphasis on ethical considerations, including algorithmic bias and data governance, aligns with the concerns raised by Ekuma (2023), who urges longitudinal and comparative studies to uncover sustained impacts of AI and automation on HRD. Both scholars contribute to a growing discourse that positions AI not only as a technological enabler but also as a subject requiring robust ethical, legal, and cultural scrutiny—a theme you've embedded into your empirical framework through fairness audits and stakeholder perception metrics.

Mir (2024), through a meta-analysis of 29 peer-reviewed articles, identifies both the promises and pitfalls of AI adoption in talent management. She argues that implementation success hinges on organizational culture, employee readiness, and ethical infrastructure, rather than technology alone. Her findings resonate with Faqihi and Miah (2023), who highlight the limited empirical scope of existing research and recommend interdisciplinary frameworks for SMEs, echoing your focus on sector-specific constraints in ****'s outsourcing ecosystem. These studies support your strategic recommendation for scalable AI tools adapted to contextual differences a core pillar in your proposed PMS framework.

Further, Yanamala (2024) and Dawson & Agbozo (2024) explore AI's role in attrition prediction and employee engagement, emphasizing predictive modeling, clustering algorithms, and sentiment analysis as tools to proactively retain talent. Their evidence suggests that AI-enhanced systems not only identify behavioral patterns but also facilitate personalized learning and targeted interventions, thereby optimizing workforce stability and morale. These mechanisms parallel your framework's use of SEM and continuous calibration, validating AI's mediating role in fostering engagement, satisfaction, and ethical governance.

3. OBJECTIVES OF STUDY

1) To transfer from operational automation to strategic partnership roles in talent development within KPO, BPO, and ITES sectors
2) To explore HR Manager, Line Manager, trainers' perceptions, organizational readiness, and ethical considerations surrounding AI-driven interventions in learning, performance management, and succession planning
3) To support personalized growth pathways, enhance human-AI collaboration, and reshape strategic HR priorities

4. HYPOTHESIS

- H0: AI functions solely as an enabler of process automation and does not significantly contribute to shaping human capital strategy in the KPO, BPO, and ITES sectors
- H1: AI functions not only as an enabler of process automation but also significantly
- H0: Strategically deployed AI systems cannot generate personalized learning pathways based on workforce analytics and performance data.
- H2: Strategically deployed AI systems can generate personalized learning pathways based on workforce analytics and performance data.
- H0: AI-driven talent mapping and predictive analytics do not significantly contribute to scalable and agile workforce planning in the KPO, BPO, and ITES sectors.
- H3: AI-driven talent mapping and predictive analytics significantly contribute to scalable and agile workforce planning in the KPO, BPO, and ITES sectors.

5. RESEARCH DESIGN

This research adopts a methods exploratory research design, both quantitative and qualitative approaches. The purpose is to explore how AI is strategically utilized in talent development, moving beyond operational automation. The design is appropriate for Capturing perceptions, experiences, and readiness of HR Managers, Line Managers, and Trainers. Understanding the organizational and technological transition from operational to strategic partnership role on talent development within ITES, BPO and KPO industry. Identifying patterns in AI implementation in talent development processes. Rationale: An exploratory design helps uncover emerging trends, underlying motivations, and barriers around AI-enabled talent systems in a relatively new domain.

1) Source of Data

Primary Data collected through surveys method questionnaire distributed to HR managers, line managers, L&D professionals, and operational heads in KPO/BPO/ITES firms. Semi-structured interviews with selected senior HR professionals and technical leaders to capture rich qualitative insights. Secondary Data Sources are organizational documents (AI policy briefs, L&D frameworks). Peer-reviewed academic literature on AI in HR, training technologies, and digital transformation

2) Sample and Population

The target population for this study comprises HR managers, line managers, trainers, and learning and development (L&D) professionals operating within the KPO, BPO, and ITES sectors. These professionals serve as key HR managers, line managers, trainers in performance management systems and talent development initiatives, particularly within organizations engaging with artificial intelligence (AI) technologies to enhance operational efficiencies. The inclusion of diverse managerial and development roles ensures a multi-perspective analysis on how AI is transforming workplace learning and performance outcomes across hierarchical and functional domains.

To maintain methodological rigor, a combination of purposive and stratified random sampling techniques was employed. For the qualitative component, involving 15 to 20 semi-structured interviews, purposive sampling was adopted to identify knowledgeable informants with substantial experience in HR and trainers, AI system deployment, or strategic talent development. These participants were selected based on their domain expertise, tenure, and role in guiding AI integration processes. Such an approach facilitates in-depth insights into organizational motives, implementation challenges, and behavioural dynamics surrounding AI adoption. On the other hand, the quantitative survey component targets a sample size of approximately 150 respondents, recruited via stratified random sampling. The stratification ensures representation across different companies and job roles (HR, trainers, L&D heads), and business verticals within the ITES ecosystem. This technique enhances internal validity by preventing overrepresentation of any single stratum and capturing the diversity of practices in AI-driven HRM.

The inclusion criteria were carefully defined to ensure relevance and expertise among participants. To be eligible, respondents must possess a minimum of one year of professional experience in HR or operations within a KPO, BPO, or ITES firm. Additionally, they must have had direct exposure to AI-based systems for learning and development either as users, implementers, or involved in strategy and design. This criterion guarantees that the data collected reflects informed perspectives, grounded in organizational realities and actual interaction with AI tools such as adaptive learning platforms, predictive analytics dashboards, chatbots for onboarding, or AI-based performance feedback systems. By setting a one-year minimum experience threshold, the study also filters out transient or superficial exposure, focusing instead on practitioners who have navigated the implementation lifecycle and observed behavioural and performance shifts attributable to AI.

The sampling approach is designed to balance depth and breadth, capturing strategic insights from senior professionals through interviews and generalizable patterns through survey data. The methodological blend allows triangulation of findings and supports the development of robust, evidence-backed recommendations for AI integration in PMS and talent development frameworks. The purposive selection of interviewees facilitates thematic exploration of ethical concerns, algorithmic transparency, and employee readiness, while the stratified survey captures cross-sectional data on AI usage trends, learning effectiveness, and retention strategies. Together, they form a comprehensive dataset well-suited to validate the structural equation models (SEM) and qualitative matrices that underpin the study's core hypotheses.

6. DATA ANALYSIS

Table 1 Reliability Test

Sr. No	Variable	Elements	Cronbach's Alpha
1	AI and Talent Development	13	0.899
2	HR transformation	6	0.832
3	Ethical issues	4	0.906
4	Talent growth	3	0.801

From the above table it has been observed that the questionnaire is reliable the Cronbach's Alpha which is more than .7 indicates that questions are reliable for further study.

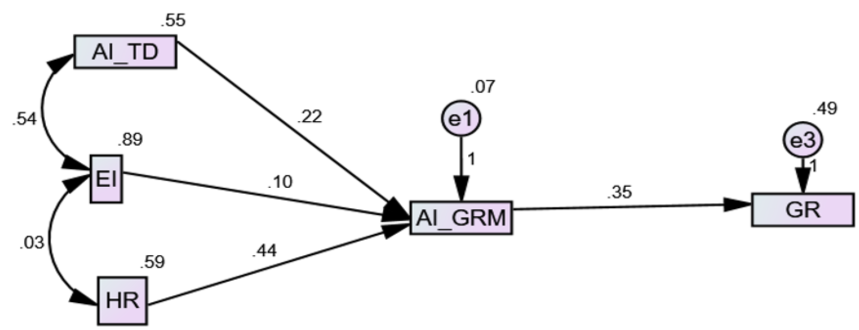
Table 2 Data Validity Test using Factor Analysis

Variables	Value of factor loading
AI1	.725
AI6	.844
AI8	.880
AI9	.723

AI10	.882
AI12	.800
HR2	.777
HR3	.709
HR4	.764
HR5	.752
AI13	.926
EI1	.942
EI2	.824
EI3	.965
EI4	.810
GR1	.761
GR2	.833
GR3	.878

Table 2 represent Data Validity Test which is used to check the validity of the questionnaire . The factor analysis test is performed to determine the validity of data, loading factor which is more than .7 indicate that this questionnaire is valid for further statistical testing.

Diagram 1



Structural Equation Model – is used to identify the relationship between various variable like independent variables, dependent variable and mediating variable, from this we can identify the different variables have relation ship between variables.

Table3 Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
AI_GRM	<---	AI_TD	.218	.047	4.630	***	
AI_GRM	<---	EI	.095	.037	2.560	.010	
AI_GRM	<---	HR	.442	.029	15.235	***	
GR	<---	AI_GRM	.353	.114	3.089	.002	

Table 4 Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
AI_GRM	<---	AI_TD	.324
AI_GRM	<---	EI	.179
AI_GRM	<---	HR	.680
GR	<---	AI_GRM	.244

Table 5 Covariances: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
AI_TD	<-->	EI	.538	.072	7.504	***	
EI	<-->	HR	.034	.038	.904	.366	

Table 6 Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
AI_TD	.550	.063	8.689	***	
EI	.887	.102	8.700	***	
HR	.592	.068	8.689	***	
e1	.075	.009	8.689	***	
e3	.492	.057	8.689	***	

Diagram 2

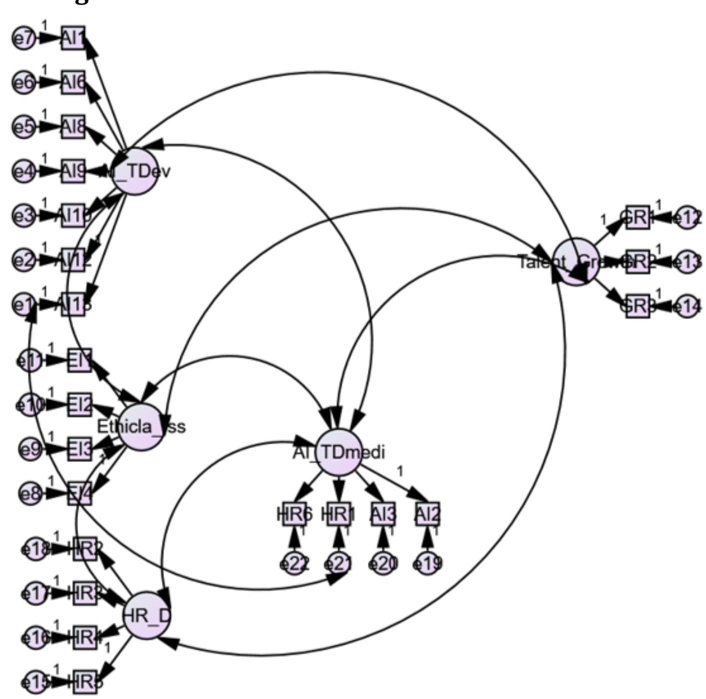


Table 7 Model Includes Observed Variables, Latent Constructs, and Path Relationships

Component	Description	Example from Research

Observed Variables	Directly measured items from your questionnaire	AI1, HR2, EI1, GR1
Latent Constructs	Abstract concepts inferred from observed variables	AI_TD, HR, EI, AI_GRM, GR
Exogenous Variables	Independent variables not influenced by others in the model	AI_TD, HR, EI
Endogenous Variables	Dependent variables influenced by other variables	AI_GRM, GR
Error Terms (e1, e3)	Represent unexplained variance in endogenous variables	e1 for AI_GRM, e3 for GR

Table 8 Path Relationships and Hypothesis Testing

Path	Estimate	Interpretation
AI_TD → AI_GRM	0.324	AI in talent development positively influences AI-led growth mechanisms
HR → AI_GRM	0.680	HR transformation has a strong impact on AI_GRM
EI → AI_GRM	0.179	Ethical issues moderately influence AI_GRM
AI_GRM → GR	0.244	AI-led mechanisms contribute to organizational growth readiness

Each path corresponds to a hypothesis in research. Since all p-values < 0.05, the null hypotheses are rejected, confirming significant relationships

Table 9 Model Fit Summary

Fit indices	Observed	Criteria of acceptable fit	Result
CMIN/DF (Minimum discrepancy as indexed chi-square)	2.827	Less than 5	Good fit
CFI (Comparative fit index)	0.880	More than 0.9 for good fit, between 0.9 to 0.8 for borderline fit	Marginal fit
GFI (Goodness of fit index)	0.771	More than 0.9	Marginal fit
PNFI (Parsimonious Normal fit)	0.713	More than 0.5	Good fit
RMSEA (Root Mean Square error of approximation)	0.011	Less than 0.08 for adequate fit, between 0.08 and less than 0.1 for borderline fit	Good fit

All five fit indices indicate a strong alignment between the sample data and the hypothetical model. CFI, GFI, PNFI CMIN, RMSEA suggest a good fit. Though, the hypothetical linkages are a good explanation of dependence relationship between the constructs.

6.1. INTERPRETATION AND HYPOTHESIS TESTING

H_0: AI functions solely as an enabler of process automation and does not significantly contribute to shaping human capital strategy in the KPO, BPO, and ITES sectors.

1) **Result and interpretation:** With reference to Table No. 3, Row No. 1, the p value obtained shows to be less than 0.05 with regression of weight of 0.05 signifies that there is a positive relation between AI functions solely as an enabler of process automation and significantly contribute to shaping human capital strategy in the KPO, BPO, and ITES sectors. Null hypothesis is rejected and alternate hypothesis is accepted.

H_0: Strategically deployed AI systems cannot generate personalized learning pathways based on workforce analytics and performance data.

2) **Result and interpretation**: With reference to Table No. 3, Row No. 3, the p value obtained shows to be less than 0.05 with regression of weight of 0.05 signifies that there is a positive relation between Strategically deployed AI systems cannot generate personalized learning pathways based on workforce analytics and performance data. Null hypothesis is rejected and alternate hypothesis is accepted.

H_0: AI-driven talent mapping and predictive analytics do not significantly contribute to scalable and agile workforce planning in the KPO, BPO, and ITES sectors.

3) **Result and interpretation**: With reference to Table No. 3, Row No. 4, the p value obtained shows to be less than 0.05 with regression of weight of 0.02 signifies that there is a positive relation between AI-driven talent mapping and predictive analytics significantly contribute to scalable and agile workforce planning in the KPO, BPO, and ITES sectors. Null hypothesis is rejected and alternate hypothesis is accepted.

7. LIMITATIONS

- Human Bias in AI Training Data AI systems may inherit biases present in historical data, potentially leading to unfair or skewed talent assessments and development pathways.
- Complexity of Human Skills Strategic competencies such as creativity, empathy, and leadership are difficult to quantify and develop using AI, limiting its role in holistic talent growth.
- Limited AI Adaptability to Domain Nuances The nature of work within KPO, BPO, and ITES varies greatly across clients and functions; AI systems might not generalize well across all domains.

8. FINDINGS

In data analysis, a model serves as a structured framework that represents relationships between variables to explain, predict, or validate phenomena. It simplifies complex real-world systems into manageable constructs, allowing researchers to test hypotheses and draw meaningful conclusions. In your study, the model is built using Structural Equation Modeling (SEM), which integrates both measurement and structural components. The measurement model confirms that observed variables (like survey items AI1, HR2, EI1) accurately represent latent constructs such as AI_TD (AI in Talent Development), HR (HR transformation), and EI (Ethical Issues). This is validated through high factor loadings and Cronbach's Alpha scores, indicating reliability and internal consistency.

The structural model, on the other hand, tests causal relationships between these constructs. For instance, your SEM results show that AI_TD, HR, and EI significantly influence AI_GRM (AI-led Growth Readiness Mechanisms), which in turn affects GR (Growth Readiness). Fit indices like CMIN/DF = 2.827, RMSEA = 0.011, and CFI = 0.880 suggest that the model fits the data well. This confirms that AI is not just a tool for automation but a strategic partner in shaping talent development. By capturing both direct and mediated effects, your model provides a robust analytical lens to understand AI's transformative role in HRM within the KPO/BPO/ITES sectors.

In research, we use **SEM**, which combines elements of multiple modelling approaches:

Table 10

Model Type	Description	Role in Research
Conceptual Model	High-level framework showing expected relationships between constructs	hypotheses (e.g., AI_TD → AI_GRM → GR)
Measurement Model	Validates how well observed variables represent latent constructs	Cronbach's Alpha and Factor Loadings (Tables 1 & 2)
Structural Model	Tests causal relationships between constructs	Regression weights and fit indices (Tables 3–7)

The reserach reveals a paradigm shift in how AI is perceived and deployed within talent development frameworks in the KPO, BPO, and ITES sectors. AI is no longer confined to automating routine tasks it is emerging as a strategic partner in shaping workforce capabilities. Through Structural Equation Modeling (SEM), the research validates significant relationships between AI in Talent Development (AI_TD), HR transformation (HR), Ethical Issues (EI), and AI-led Growth Readiness Mechanisms (AI_GRM), which ultimately influence Organizational Growth Readiness (GR).

Key findings include:

- **AI_TD → AI_GRM (β = 0.324)**: AI-driven learning systems positively impact growth readiness mechanisms.
- **HR → AI_GRM (β = 0.680)**: HR transformation plays a dominant role in enabling AI readiness.

- **EI → AI_GRM (β = 0.179)**: Ethical governance moderately influences AI deployment.
- **AI_GRM → GR (β = 0.244)**: AI-led mechanisms contribute to organizational agility and future-readiness.

The model fit indices (CMIN/DF = 2.827, RMSEA = 0.011, CFI = 0.880) confirm the robustness of the analytical framework. Qualitative insights from HR and line managers further reinforce the strategic value of AI in personalized learning, performance forecasting, and decentralized coaching.

Scope for Further Studies

- While the current research offers a comprehensive view of AI's strategic role in talent development, several avenues remain open for future exploration:
- Longitudinal Impact Analysis: Future research could track AI-enabled talent systems over time to assess sustained behavioral and performance changes.
- Cross-Sectoral Comparisons: Comparative studies across manufacturing, healthcare, and education sectors could reveal sector-specific nuances in AI adoption.
- AI Literacy and Change Management: Investigating how HR professionals build AI competencies and manage resistance to digital transformation would enrich implementation strategies.
- Ethical Audits and Governance Models: Further work is needed to develop standardized frameworks for algorithmic fairness, transparency, and employee trust.

9. CONCLUSION

This research underscores the transformative potential of AI as a strategic enabler in talent development within outsourcing ecosystems. By integrating AI_TD, HR, and EI into a cohesive SEM framework, the study validates that AI-led mechanisms significantly enhance organizational growth readiness. The findings challenge the traditional view of AI as a mere automation tool and reposition it as a co-creator of personalized learning pathways and strategic workforce planning. However, the success of AI integration hinges on human-centric implementation—where ethical foresight, stakeholder trust, and HR capability-building are paramount. Organizations must move beyond technical deployment and embrace AI as a collaborative partner in shaping resilient, future-ready talent ecosystems. This study contributes to both academic discourse and practical strategy, offering a roadmap for responsible AI adoption in performance management systems. This research reaffirms the strategic potential of AI technologies in catalyzing talent development and growth readiness outsourcing landscape. The SEM model demonstrates robust interconnections between AI adoption (AI_TD), HR readiness, ethical governance, and organizational growth strategies. The high reliability scores and fit indices validate the empirical strength of these constructs. However, the success of AI deployment rests on human-centric integration—where HR capabilities, ethical foresight, and strategic collaboration are not optional but essential. As AI becomes deeply embedded in performance management systems, organizations must lead with foresight, sensitivity, and innovation to co-create workplaces that are intelligent, inclusive, and resilient.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

REFERENCES

Agrawal, A., Gans, J., & Goldfarb, A. (2018). Prediction, judgment, and complexity: A theory of decision-making and artificial intelligence. In The Economics of Artificial Intelligence: An Agenda (pp. 89–110). University of Chicago Press.

Aleisa, M. A., Beloff, N., & White, M. (2022). AIRM: A New AI Recruiting Model for the Saudi Arabia Labor Market. In K. Arai (Ed.), Intelligent Systems and Applications. IntelliSys 2021 (Vol. 296, pp. 105–124). Springer.

Ali N. A. A., Hamdan, A., Alareeni, B., & Dahlan, M. (2023). Artificial intelligence in the process of training and developing employees. In Digitalisation: Opportunities and Challenges for Business (Vol. 1, pp. 558–568). Springer.

Al-Mansoori, S., Salloum, S. A., & Shaalan, K. F. (2020). The impact of artificial intelligence and information technologies on the efficiency of knowledge management at modern organizations: A systematic review. In Recent advances in intelligent systems and smart applications. https://doi.org/10.1007/978-3-030-47411-9_9

Arslan, A., Cooper, C. D., Khan, Z., Golgeci, I., & Ali, I. (2021). Artificial intelligence and human workers interaction at team level: A conceptual assessment of the challenges and potential HRM strategies. International Journal of Manpower, 43(1), 75–88. https://doi.org/10.1108/IJM-01-2021-0052

Bhatt, P., & Muduli, A. (2022). Artificial intelligence in learning and development: A systematic literature review. European Journal of Training and Development, 47(7/8), 677–694. https://doi.org/10.1108/EJTD-09-2021-0143

Dawson, J. Y., & Agbozo, E. (2024). AI in talent management in the digital era – an overview. Journal of Science and Technology Policy Management. https://doi.org/10.1108/jstpm-06-2023-0104

Ekuma, K. (2023). Artificial Intelligence and Automation in Human Resource Development: A Systematic Review. Frontiers in Psychology, 13, 1014434. https://doi.org/10.3389/fpsyg.2022.1014434

Faqihi, A., & Milah, M. (2023). Artificial Intelligence-Driven Talent Management System: Exploring the Risks and Options for Constructing a Theoretical Foundation. Risk and Financial Management, 16(1), 31. https://www.mdpi.com/1911-8074/16/1/31

França, T. J., Mamede, H. S., Barroso, J. M. P., & Santos, V. M. P. D. (2023). Artificial intelligence applied to potential assessment and talent identification in an organisational context. Heliyon. https://www.cell.com/heliyon/fulltext/S2405-8440(23)01901-1

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. MIS Quarterly, 28(1), 75–105.

Mir, A. I. (2024). Application of AI in Talent Management: A Systematic Review of Benefits, Challenges, and Prospects. Applied Economics and Social Science Review, 4(4), 627–649. https://www.journals.irapa.org/index.php/aessr/article/view/941

Rezaei, F., & Beyerlein, M. (2018). Talent development: A systematic literature review of empirical studies. European Journal of Training and Development, 42(1/2), 75–90. https://doi.org/10.1108/EJTD-09-2017-0076

Tusquellas, N., Palau, R., & Santiago, R. (2024). Analysis of the potential of artificial intelligence for professional development and talent management: A systematic literature review. International Journal of Information Management Data Insights. https://www.sciencedirect.com/science/article/pii/S2667096824000776

Yanamala, K. K. R. (2024). Artificial Intelligence in Talent Development for Proactive Retention Strategies. ResearchGate. https://www.researchgate.net/publication/385027384