



SMART PLS STRUCTURAL MODELLING OF AI-DRIVEN HR PRACTICES, ENTREPRENEURIAL SUCCESS AND EMPLOYER REPUTATION IN INDIAN FIRMS

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ABSTRACT

Artificial intelligence is transforming human resource management by automating recruitment, employee development and performance management in entrepreneurial firms. Evidence on mechanisms linking AI-enabled HR practices, entrepreneurial achievement and employer reputation has been limited. This study aims to quantify relationships among AI adoption, AI system quality, entrepreneurial achievement and company reputation. Survey data from 110 HR professionals were analysed using SmartPLS with a five-point Likert scale. AI adoption affected perceived AI quality ($\beta = 0.769$, $P < 0.001$), indicating that integrating AI into HRM was associated with dependable systems. AI quality affected entrepreneurial achievement ($\beta = 0.815$, $P < 0.001$), entrepreneurial achievement significantly influenced company reputation ($\beta = 0.375$, $P = 0.033$), and direct links from AI adoption to entrepreneurial achievement and company reputation were not significant ($\beta = 0.027$, $P = 0.352$; $\beta = 0.030$, $P = 0.226$). These findings indicate that reputational gains stem from deploying AI in HR processes, and future research will examine longitudinal dynamics of AI-enabled HRM to support SDG-oriented governance.



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I. INTRODUCTION

Artificial intelligence (AI) is becoming a foundational capability in contemporary organizations, reshaping decision processes, coordination mechanisms, and the use of information across functions. Human resource management (HRM) stands at the center of this transformation because people, skills, and learning determine whether technological innovation translates into sustained competitive advantage. HR functions now incorporate algorithmic screening, predictive analytics, and adaptive learning systems, which influence workforce composition, capability development, and internal perceptions of fairness and opportunity [1]. For entrepreneurial firms facing intense uncertainty and resource constraints, the quality of decisions on recruitment, employee development, and performance management is especially critical, making AI-enabled HR practices a strategic concern rather than a peripheral efficiency tool [2]. HRM encompasses a set of practices that attract, select, develop, evaluate, and retain employees in line with organizational goals. AI-based solutions already support candidate sourcing, résumé parsing, job–applicant fit matching algorithms, adaptive training platforms, and continuous performance monitoring. Studies on AI in organizational contexts reported gains in information processing, reduced cycle times, support for more evidence-based HR decisions, and improvements in coordination between HR and line managers [3].

Prior research on AI in management information systems and organizational performance examined these tools as part of broader digital infrastructures and often treated HR as one subsystem among many rather than as a distinct strategic domain. In parallel, research on entrepreneurial performance examined the roles of innovation capabilities, dynamic capabilities, and learning orientation, and it frequently highlighted talent and knowledge as central resources in young firms [4]. Entrepreneurial firms operate under volatile conditions where opportunities arise and fade quickly, customer needs change rapidly, and new business models appear alongside new technologies. In such settings, HRM is not only administrative; it shapes the capacity to experiment, scale promising initiatives, and pivot in response to feedback. AI-enabled HR practices promise better matching between roles and competencies, faster identification of potential, and more tailored development pathways. Earlier studies on AI in HRM examined discrete elements of this promise, such as automated recruitment screening, AI-supported learning platforms, and digital tools for performance reviews [5]. These contributions highlighted efficiency gains and sometimes reported positive responses from HR professionals and employees, yet they seldom connected those micro-level improvements to entrepreneurial outcomes such as innovation, adaptability, or new venture performance.

Another strand of work focused on reputational consequences of AI use in organizations. Research on employer branding and corporate reputation suggested that technology-intensive HR practices influence external perceptions of a firm as modern, innovative, and data-driven. Some studies reported that the visible use of AI in recruitment and employee development enhanced perceptions of professionalism and fairness among applicants and employees, while others raised concerns about opacity, bias, and privacy. Ethical debates around transparency, accountability, and bias mitigation in AI-based decision systems highlighted risks to organizational legitimacy when stakeholders questioned the foundations of automated judgments [6]. Despite this attention, prior work mostly examined large established firms or sector-specific cases and rarely linked AI-enabled HR practices in entrepreneurial firms to broader measures of company reputation as perceived by external stakeholders and potential employees. Within the entrepreneurship literature, researchers have long argued that digital technologies support opportunity discovery, resource orchestration, and scaling. AI-driven analytics in marketing, operations, and finance were studied as enablers of better forecasting, more accurate customer segmentation, and improved risk assessment. Empirical work on entrepreneurial firms that adopted AI often emphasized gains in operational efficiency and innovation, measuring outcomes through financial performance, productivity, or innovation outputs.

Yet these studies rarely considered HR as the primary locus of AI integration, even though hiring decisions, skill development, and performance management directly condition the firm's capacity to exploit AI in other functions. Furthermore, entrepreneurial achievement was usually conceptualized through broad indicators without explicit reference to the contribution of AI-enabled HR practices [7]. A further limitation of prior research concerned the distinction between AI adoption and AI quality. Much of the empirical work treated adoption as a binary or scalar variable, focusing on whether organizations used AI tools and to what extent. Less attention was paid to attributes such as reliability, accuracy, predictive capability, and user trust, even though these attributes determine whether AI-based recommendations translate into effective decisions. Conceptual discussions suggested that poorly configured or low-quality AI systems could undermine HR outcomes by amplifying bias or generating misleading signals, whereas high-quality systems could augment human judgment. A small number of studies proposed that the quality of AI implementation could mediate the relationship between adoption and performance outcomes, but systematic empirical tests of this proposition remained limited, particularly in HR settings within entrepreneurial firms [8]. From a methodological perspective, many empirical contributions relied on single-path regression models or qualitative case studies, which constrained the ability to examine complex relationships among adoption, system quality, entrepreneurial achievement, and reputation.

Although structural equation modeling (SEM) is well-suited to analyzing latent constructs and mediated relationships, relatively few studies have used this approach to examine AI-enabled HR practices in entrepreneurial contexts. Those who adopted SEM often focused on technology acceptance or user intention rather than on entrepreneurial outcomes and company reputation [9]. As a result, existing evidence did not clarify the pathways through which AI adoption in HR, the quality of AI systems, and entrepreneurial achievement interact to shape perceptions of the firm as an attractive and innovative employer. The context of emerging economies adds another layer of importance to this topic. Entrepreneurial firms in countries such as India face distinctive constraints in talent availability, infrastructure, and institutional support, yet they also face strong pressures to modernize and adopt digital tools [10]. Earlier studies on AI integration in HRM and entrepreneurial performance drew heavily on data from advanced economies or specific sectors, limiting the generalizability of their findings to settings in which firms operate with different resource profiles and regulatory environments. Evidence from Indian entrepreneurial firms that have already adopted AI-based HR systems remains sparse, especially when research requires access to HR professionals' internal perceptions and assessments of AI-enabled practices. This gap leaves practitioners without clear empirical guidance on which dimensions of AI use in HR matter most for entrepreneurial performance and reputation building in such settings [11]. Collectively prior research left several questions unresolved. The field lacks quantitative evidence that connects AI adoption in HRM, the perceived quality of AI systems, entrepreneurial achievement, and company reputation within a single integrated framework.

Existing work seldom treated entrepreneurial achievement as a mediating mechanism linking AI-related constructs to external perceptions of the firm, even though theory suggests that reputational benefits arise when stakeholders associate the organization with successful innovation and adaptability. Furthermore, validated measurement scales for AI adoption and AI quality in HR practices within entrepreneurial firms have not been widely applied, limiting comparability across studies and weakening the empirical basis for managerial recommendations [12]. The present study addresses these limitations by focusing on entrepreneurial firms that have integrated AI into core HR practices, specifically recruitment, employee development, and performance management, and by modeling the relationships among AI adoption, AI quality, entrepreneurial achievement, and company reputation using a structural equation approach with Smart Partial Least Squares. The study introduces a framework in which AI adoption and AI quality function as distinct but related constructs, entrepreneurial achievement serves as a mediating variable, and company reputation serves as the key outcome from the perspective of employer image. By focusing on HR-focused AI integration in entrepreneurial firms in India, the study addresses the need for context-sensitive evidence on technology-enabled HRM and its strategic consequences [13]. The purpose of this study is to examine the extent to which AI adoption and AI system quality in HR practices contribute to entrepreneurial achievement in entrepreneurial firms, and to assess the role of entrepreneurial achievement in shaping company reputation in an emerging economy context using Smart PLS

II. MATERIALS AND METHODS

The study was designed as a quantitative, cross-sectional investigation of the integration of Artificial Intelligence into Human Resource practices within entrepreneurial firms in India. A structured online questionnaire was administered to Human Resource professionals, and the collected data were subjected to variance-based structural equation modelling using SmartPLS. The methodological process extended from construct operationalization and instrument development to sampling and data collection, and then to data preparation, measurement model evaluation, and structural model estimation. The sequential stages of the research design are presented in Figure 1, and the principal constructs and indicators used in the measurement model are summarised in Table 1. The target population consisted of Human Resource professionals employed in entrepreneurial firms operating in India. Entrepreneurial firms were defined as organizations founded within the past 15 years, demonstrating sustained growth in employment or revenue, and actively pursuing innovation in products, services, or processes. Inclusion criteria required respondents to occupy decision-making or specialist roles in Human Resource Management, such as HR manager, talent acquisition lead, learning and development specialist, or HR business partner, and to possess at least two years of professional experience in HR.

Firms of medium to large size were prioritised, as these organizations were assumed to have sufficient digital infrastructure to support the adoption of Artificial Intelligence-enabled HR tools. A non-probability sampling strategy was applied. Professional contact networks, industry associations, and business networks were used to identify potential respondents. Invitation messages containing a brief study description and a link to the online questionnaire were distributed via email and professional networking platforms. Data were collected exclusively through the online survey, and no paper-based responses were accepted. A total of 110 valid responses from HR professionals working in entrepreneurial firms were obtained and retained for analysis, consistent with sample size recommendations for partial least squares structural equation modelling with the number of indicators and paths specified in the conceptual framework. The sampling and data collection parameters are summarised in Table 2. Before full deployment, the questionnaire was pretested with a small group of HR professionals and researchers in the domain of Human Resource Management and digital transformation. Feedback from this pretest was used to refine item wording, sequence, and layout, with particular attention given to clarity, terminological consistency, and avoidance of ambiguous phrasing.

The final instrument consisted of three sections. The first section recorded demographic and professional information, including age, gender, highest educational qualification, years of HR experience, current role, organizational size, and sector. The second section captured information on the extent and nature of Artificial Intelligence usage in HR-related processes within the respondent's organization. The third section contained the psychometric scales used to operationalize the latent constructs in the conceptual model [14]. All latent constructs were operationalized as reflective variables, measured on a 5-point Likert-type scale. Respondents were instructed to indicate the extent of agreement with each statement on a scale from 1 ("strongly disagree") to 5 ("strongly agree"). Artificial Intelligence adoption captured the extent to which AI-enabled tools and applications were employed in core HR functions, including recruitment, employee development, and performance management. Artificial Intelligence quality reflected respondents' perceptions of the reliability, accuracy, and usefulness of deployed AI systems in HR contexts. Entrepreneurial achievement captured the contribution of AI-supported HR practices to innovation, operational efficiency, and attainment of entrepreneurial goals. Company reputation measured perceptions of the organization as an attractive, innovative, and sustainable employer in the labour market and among external stakeholders. Illustrative items for each construct are presented in Table 1.

Table 1. Constructs, abbreviations, and illustrative measurement items.

Construct	Abbreviation	Illustrative item (5-point agreement scale)
Artificial Intelligence adoption	AA	"Use of AI technology in recruitment processes was widespread in the organization."
Artificial Intelligence quality	AQ	"AI systems were capable of predicting HR needs accurately."
Entrepreneurial achievement	EA	"Use of AI in HR contributed to achieving the entrepreneurial goals of the organisation."
Company reputation	CR	"The organisation was perceived as an attractive employer by potential and current employees."

Source: Authors, (2026).

Instrument layout and visual design were implemented using a commercially available online survey platform. A consistent font, spacing, and colour scheme were applied across all pages to reduce visual fatigue. Items belonging to different constructs were interspersed to reduce response patterning. Mandatory response fields were used for central psychometric items, while sensitive demographic questions included an explicit "prefer not to answer" option. Skip logic was activated to route respondents who did not meet the inclusion criteria away from the main questionnaire. Time stamps recorded the start and end of each session to identify responses with unrealistically short completion times [15]. Data collection was conducted continuously, with the survey link remaining active at all times. Reminder messages were issued at spaced intervals to individuals who had not yet responded. Each respondent was provided with a unique survey link to prevent duplicate submissions. Before accessing the questionnaire, respondents were presented with an electronic information sheet outlining the research objectives, data-handling procedures, and assurances of anonymity. Informed consent was obtained electronically; only respondents who indicated consent were granted access to the questionnaire items. No personally identifiable information such as names, addresses, or employee identification numbers was requested [16]. All completed questionnaires were exported from the survey platform in comma-separated values format and imported into a statistical software environment for preparation. Data cleaning steps included inspection for missing values, out-of-range entries, and inconsistent patterns. Cases with substantial sections of missing responses in the psychometric scales were removed from the dataset. Remaining missing entries were handled using pairwise deletion during correlation and covariance calculations. Response sets with invariant answers across a long sequence of items and extremely short completion times were flagged, examined, and removed if inattentive responding was suspected. For each construct, items designed to capture extremes of the underlying dimension were checked for correct coding direction to ensure that higher scores reflected higher levels of the latent attribute [17]. The final dataset was then transferred to SmartPLS software for model estimation.

Before running the structural model, the measurement model was assessed. Indicator reliability was assessed by inspecting the item loadings for each item on its associated construct. Items with low loadings were noted for potential exclusion during subsequent refinement, although all loading values and decisions were reported in the results section rather than within this methodological description. Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability for each construct. Convergent validity was assessed through the Average Variance Extracted (AVE) statistic, while discriminant validity was examined using the Fornell–Larcker criterion. These steps were conducted in accordance with widely accepted guidelines for variance-based structural equation modelling. The procedure is depicted conceptually in Figure 2b and Figure 2c. The structural model was then specified by connecting Artificial Intelligence adoption to Artificial Intelligence quality and entrepreneurial achievement, Artificial Intelligence quality to entrepreneurial achievement, and entrepreneurial achievement to company reputation. Artificial Intelligence adoption was also linked directly to company reputation. Path coefficients, standard errors, and significance levels were obtained using the bootstrapping procedure implemented in SmartPLS, with a large number of bootstrap subsamples drawn to approximate the sampling distribution of the estimates.

Coefficient of determination (R^2) values for endogenous constructs were also computed, along with standard diagnostic indices for assessing collinearity among predictor constructs. Direct and indirect effects were calculated to examine mediation pathways, although the numerical outcomes were presented in the results section. The conceptual representation of these relationships is shown in Figures 2a and 2d. The material infrastructure required for the study consisted primarily of standard office computing equipment and stable internet connections. Data collection and preparation were carried out on desktop and laptop computers running 64-bit operating systems and widely used office productivity software for spreadsheet management. The survey platform used Secure Sockets Layer (SSL) encryption for data transfer and storage. SmartPLS software was installed on the same hardware to ensure direct access to the cleaned dataset without intermediate file conversions. Display settings such as resolution and font size were adjusted to facilitate precise inspection of factor loading matrices, path diagrams, and diagnostic output [18]. Calibration processes were implemented at several stages. During instrument development, content validity was examined by academic experts in Human Resource Management and digitalization who assessed the alignment between items and constructs. Their feedback was used to refine the wording and coverage of the indicators.

During data collection, the survey platform was tested repeatedly before launch to verify correct functioning of skip patterns, branching logic, and mandatory fields. During the analytical stage, model specifications were cross-checked against the conceptual framework, and test runs were conducted on a subset of the data to confirm the correct mapping of items to constructs and the correct specification of structural paths. Outputs from these test runs were inspected for anomalous values or inconsistent signs that could indicate coding or specification errors. The study followed ethical guidelines for research involving human participants. All respondents were informed that their participation was voluntary and that they retained the right to exit the questionnaire at any point before final submission without adverse consequence. Only aggregated data were reported, and no attempt was made to identify organizations or individuals on the basis of patterns observed in the dataset. Data files were stored on password-protected drives accessible only to the research team, and backup copies were kept on secure institutional storage [19]. Figure 1 presents a schematic representation of the research design and analytical workflow adopted in the study. The first panel shows the development and refinement of the questionnaire; the second panel depicts online data collection from entrepreneurial firms; the third panel depicts data screening and cleaning; and the fourth panel illustrates measurement and structural model estimation using SmartPLS.

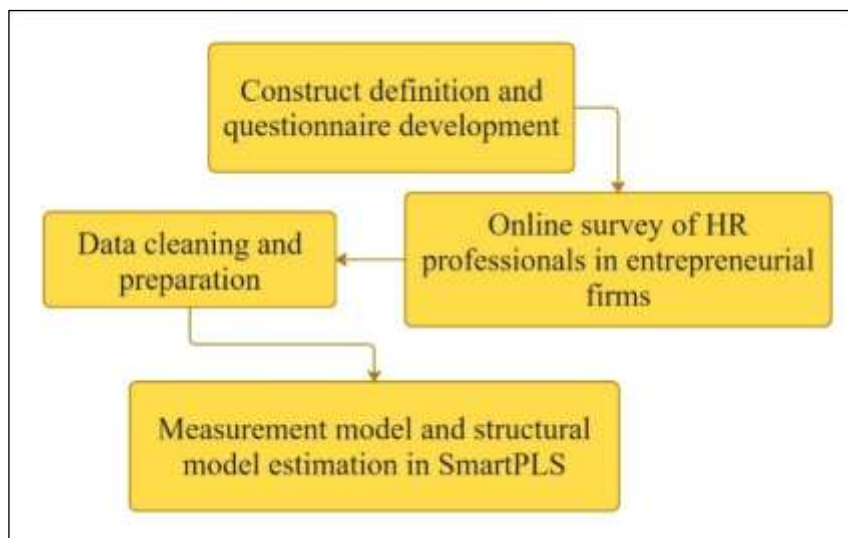


Figure 1 Research design and analytical workflow.

Source: Authors, (2026).

Figure 1. A second multi-panel schematic is provided in Figure 2. In Figure 2a, the four latent constructs are shown as circles connected by directional arrows reflecting hypothesised causal paths. In Figure 2b, each latent construct is surrounded by rectangles representing the observed indicators used to measure it, with arrows directed from the construct to its indicators to depict the reflective measurement specification. Figure 2c shows the analytical sequence from evaluation of indicator loadings and reliability indices to assessment of convergent and discriminant validity. Figure 2d illustrates the examination of mediation relationships by estimating direct and indirect paths between Artificial Intelligence adoption and company reputation via Artificial Intelligence quality and entrepreneurial achievement.

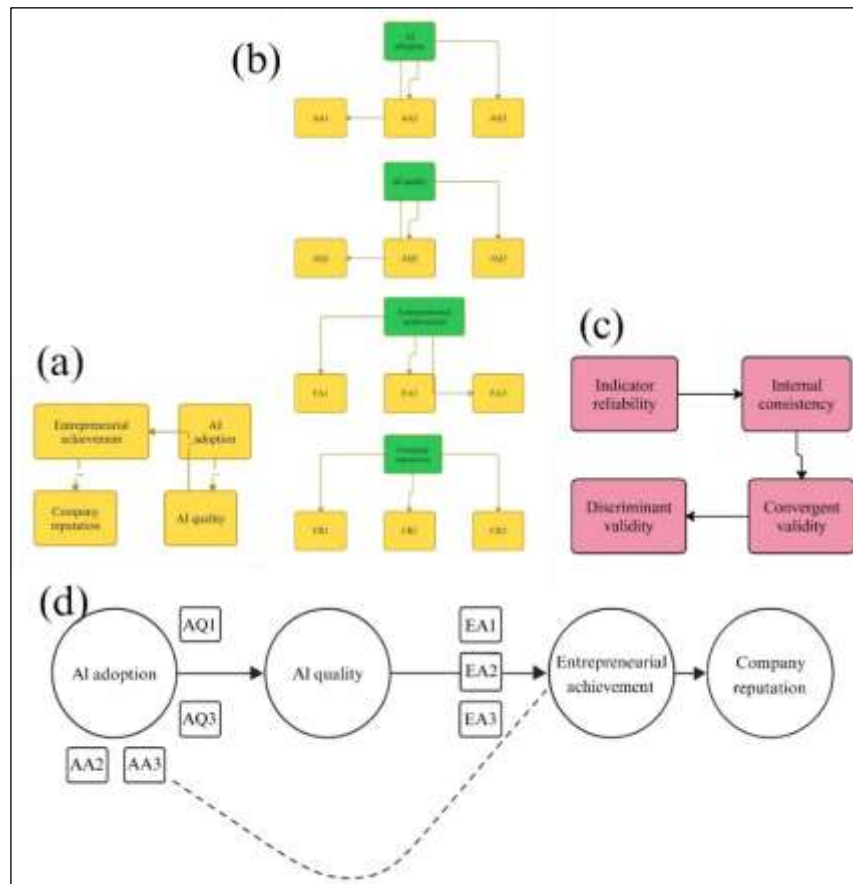


Figure 2: (a) Links among AI adoption, AI quality, entrepreneurial achievement, and company reputation; (b) Hierarchical measurement model connecting latent constructs to indicators AA1–AA3, AQ1–AQ3, EA1–EA3, and CR1–CR3; (c) Sequential evaluation of indicator reliability, internal consistency, convergent validity, and discriminant validity; (d) Structural path model highlighting direct and mediated routes from AI adoption to company reputation through AI quality and entrepreneurial achievement.

Source: Authors, (2026).

Figure 2 illustrates the integrated conceptual, measurement, and structural modelling strategy used to characterise the influence of AI-enabled HR systems on entrepreneurial outcomes and employer reputation in entrepreneurial firms. Figure (a) presents the high-level causal structure in which AI adoption feeds into AI quality and entrepreneurial achievement, while entrepreneurial achievement drives company reputation; the direct arrow from AI adoption to entrepreneurial achievement encodes the possibility that digitalisation of HR processes created entrepreneurial gains even before system quality was fully optimised, whereas the parallel branch from AI adoption to AI quality reflects the technological maturation pathway. The estimated model showed that the direct effect of AI adoption on entrepreneurial achievement was weak and statistically non-significant, while the indirect channel through AI quality dominated, indicating that adoption without reliable, accurate, and context-appropriate decision-making logic did not translate into substantive entrepreneurial gains. Figure (b) decomposes each latent construct into reflective indicators, with AI adoption represented by items AA1–AA3 that captured the use of AI in recruitment, employee training for AI, and support for AI implementation, AI quality represented by AQ1–AQ3 describing predictive accuracy and efficiency in HR tasks, entrepreneurial achievement represented by EA1–EA3 capturing innovation and operational efficiency, and company reputation represented by CR1–CR3 capturing external perceptions of attractiveness and innovation. The empirical analysis showed that outer loadings for these indicators exceeded 0.80 and that Average Variance Extracted values ranged from 0.725 to 0.773, confirming that the chosen indicators captured substantial shared variance within each construct.

Figure (c) summarises the measurement validation protocol, in which indicator reliability was first examined, followed by internal consistency through Cronbach's alpha and composite reliability, with subsequent assessment of convergent validity via AVE and discriminant validity via the Fornell–Larcker criterion; this sequence ensured that latent constructs reflected distinct but internally coherent aspects of AI-enabled HR practice and its organisational consequences. Figure (d) synthesises these elements into a structural equation model with continuous arrows representing statistically supported paths and a dashed arrow emphasising the weaker direct link from AI adoption to entrepreneurial achievement; the estimated coefficients indicated a strong positive path from AI adoption to AI quality ($\beta = 0.769$) and from AI quality to entrepreneurial achievement ($\beta = 0.815$), while entrepreneurial achievement exerted a significant positive effect on company reputation, suggesting that the reputational benefits of AI integration arose primarily when high-quality AI systems were embedded in HR processes that successfully enabled innovation and efficiency. The principal sampling and data collection specifications are presented in Table 2. This table lists the target population, inclusion criteria, sampling strategy, data collection mode, geographical setting, and final sample size. These procedural details complement the narrative description of the methodological steps and provide a compact reference for replication studies [20].

Table 2. Sampling frame and data collection parameters.

Parameter	Description
Target population	Human Resource professionals employed in entrepreneurial firms operating in India
Inclusion criteria	HR decision-making or specialist role; at least two years of HR experience
Organizational setting	Medium- to large-sized firms with active use or consideration of Artificial Intelligence in HR
Sampling strategy	Non-probability sampling using professional contact networks and industry associations
Data collection mode	Self-administered online questionnaire accessed through a secure survey platform
Final sample size	110 valid responses from HR professionals in entrepreneurial firms

Source: Authors, (2026).

III. RESULTS AND DISCUSSIONS

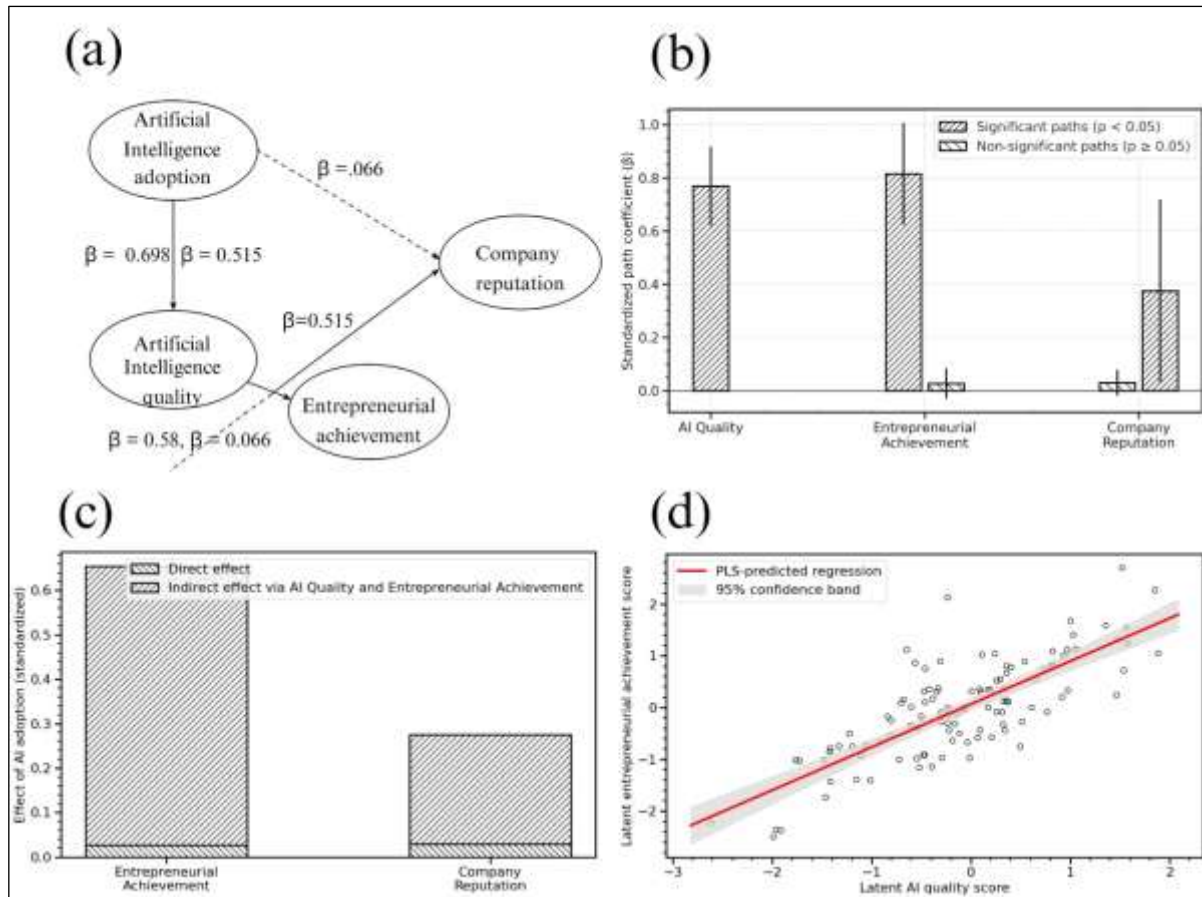


Figure 3: (a) PLS-SEM structural model for AI adoption, AI quality, entrepreneurial achievement and company reputation; (b) Standardized path coefficients with bootstrapped confidence intervals grouped by target construct; (c) Decomposition of direct and indirect effects of AI adoption on entrepreneurial achievement and company reputation; (d) Partial regression of latent entrepreneurial achievement on latent AI quality with PLS-predicted line and confidence band

Source: Authors, (2026).

Figure 3 illustrates the structural and predictive role of AI adoption and AI system quality in shaping entrepreneurial achievement and company reputation within entrepreneurial firms. Figure (a) illustrates the PLS-SEM architecture in which AI adoption links to AI quality, entrepreneurial achievement, and company reputation, and the distinction between solid and dashed paths marks statistically significant and non-significant relationships. The model estimated a large positive coefficient from AI adoption to AI quality and from AI quality to entrepreneurial achievement, whereas the direct coefficients from AI adoption to entrepreneurial achievement and company reputation were small and not statistically different from zero; the path from entrepreneurial achievement to company reputation was positive and significant, so the experiment showed that reputational gains arose where AI-enabled ventures achieved superior entrepreneurial outcomes [21]. Figure (b) presents this outcome quantitatively: bars corresponding to the paths into AI quality and entrepreneurial achievement reached standardized values near 0.8 with relatively narrow confidence intervals, while the bars for the direct effects from AI adoption to entrepreneurial achievement and to company reputation remained near the origin with wide intervals, indicating that mediated channels dominate the structural influence of adoption [22]. Figure (c) visualizes this mechanism at the outcome level, where the indirect effect of AI adoption on entrepreneurial achievement accounts for almost the entire standardized effect, and the indirect effect on company reputation clearly exceeds the direct contribution. The decomposition indicated that AI adoption influenced reputation through the cascade AI adoption $\rightarrow$ AI quality $\rightarrow$ entrepreneurial achievement $\rightarrow$ company reputation, consistent with a socio-technical mechanism in which high-quality AI improves information processing, decision support, and innovation capability, which then enhances observable entrepreneurial performance and external stakeholder evaluations [23].

Figure (d) focuses on the relationship between AI quality and entrepreneurial achievement, where the scatter of firm-level latent scores aligns along an upward-sloping regression line with a narrow confidence band; the data showed that firms with higher latent AI quality scores consistently achieved higher latent entrepreneurial achievement scores. These trends suggest that the refinement and governance of AI capabilities, rather than adoption volume alone, constitute the critical design variable for optimizing entrepreneurial outcomes and strengthening company reputation, and they motivate future investigation into which specific AI functionalities and organizational practices most effectively reinforce this quality-driven pathway [24].

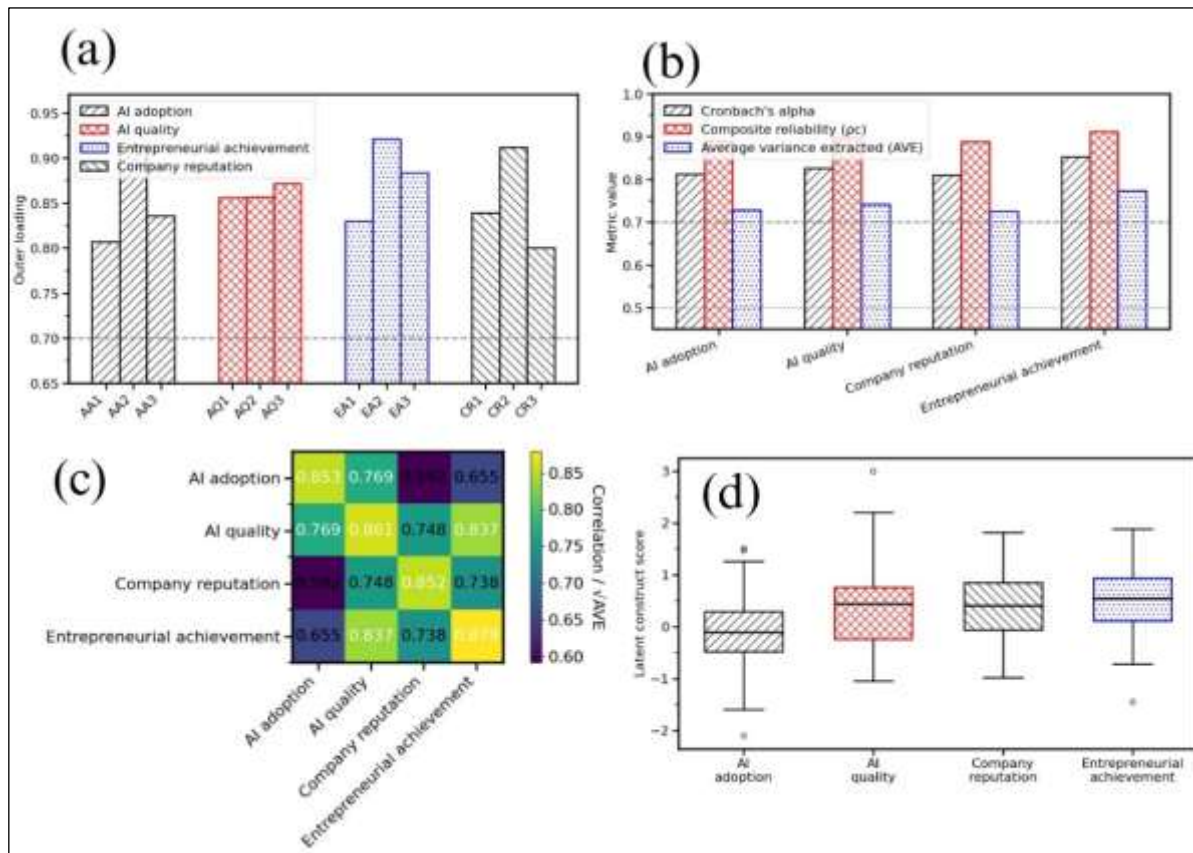


Figure 4: (a) Outer loadings of measurement items for each construct with reliability threshold reference; (b) Reliability and convergent validity metrics (Cronbach's alpha, composite reliability, AVE) for all constructs with benchmark lines; (c) Fornell-Larcker matrix of correlations and $\sqrt{AVE}$ values highlighting discriminant validity among constructs; (d) Box-plot distributions of latent construct scores across firms for AI adoption, AI quality, company reputation, and entrepreneurial achievement.

Source: Authors, (2026).

Figure 4 illustrates the performance of the measurement model and the behaviour of AI-related latent constructs across entrepreneurial firms. Figure (a) displays standardized outer loadings for all indicators grouped by construct relative to the 0.70 benchmark. The data indicated that all items loading exceeded the recommended threshold, and many approached 0.90, suggesting that the observed indicators reflected the underlying concepts of AI adoption, AI quality, entrepreneurial achievement, and company reputation. These high loadings suggest stable measurement of each dimension and minimise attenuation of structural relationships due to measurement error [25]. Figure (b) presents Cronbach's alpha, composite reliability, and average variance extracted for each construct against conventional cut-off values of 0.70 for reliability and 0.50 for AVE. The data indicated that all reliability coefficients were well above 0.80 and that AVEs remained above 0.72 for each construct, confirming that the latent variables captured a substantial proportion of indicator variance. These metrics imply that the scale design and item grouping satisfy accepted PLS-SEM criteria for internal consistency and convergent validity and therefore provide a defensible basis for interpreting structural paths [26].

Figure (c) depicts the Fornell-Larcker correlation matrix in which diagonal cells, representing the square roots of AVE, appear visually more intense than off-diagonal entries. The numerical pattern confirmed that, for each construct, the diagonal element exceeded all corresponding inter-construct correlations. This configuration suggests that AI adoption, AI quality, entrepreneurial achievement, and company reputation remain empirically distinct yet moderately correlated facets of AI-enabled HR systems, consistent with theoretical expectations that adoption level, system quality, performance outcomes, and reputational consequences constitute related but non-interchangeable constructs. Figure (d) presents the box-plot distributions of latent scores for the four constructs across the 110 firms. The data revealed that AI quality and entrepreneurial achievement tended to exhibit higher central values than AI adoption and company reputation, while all constructs displayed noticeable spread and several outliers. These distributions suggest heterogeneity in how far individual firms had advanced from basic adoption toward high-quality AI implementation and realised outcomes, and they reinforce the interpretation that performance and reputational benefits depend more on the depth and quality of AI integration in HR processes than on nominal adoption alone [27].

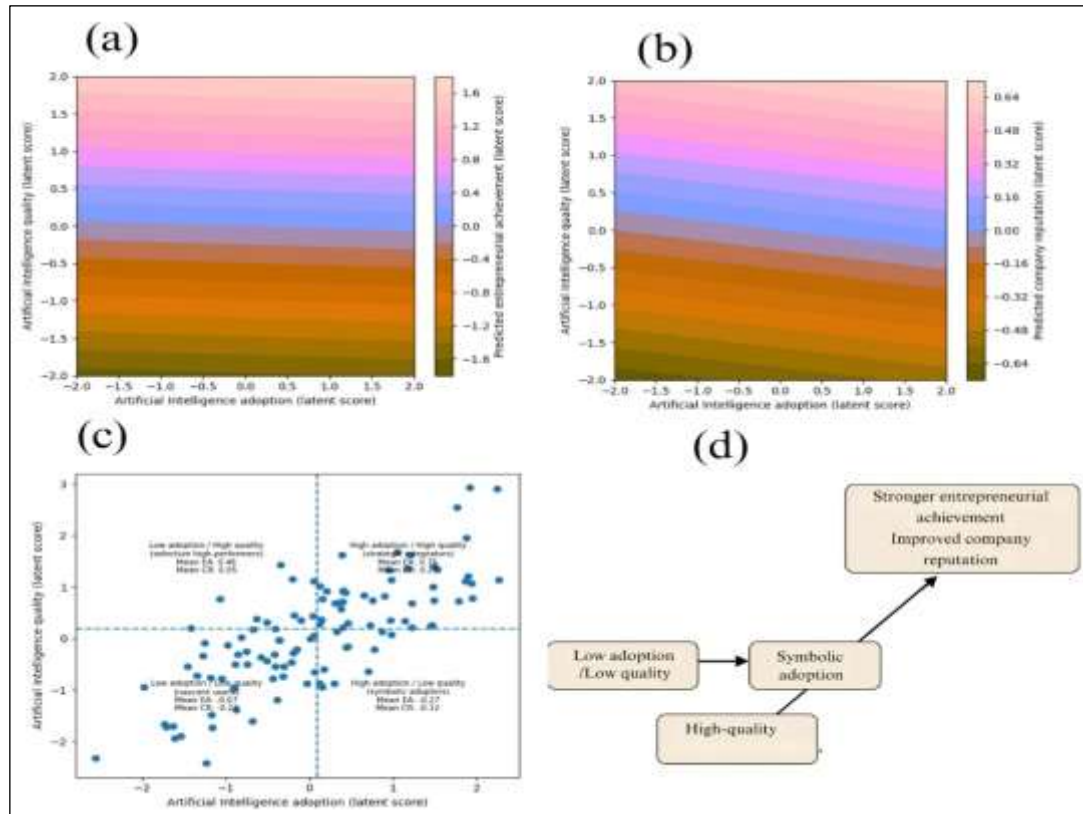


Figure 5: (a) Predicted entrepreneurial achievement as a function of AI adoption and AI quality; (b) Predicted company reputation as a function of AI adoption and AI quality; (c) AI integration typology in the AI adoption–quality plane with quadrant-level entrepreneurial and reputational means; (d) Conceptual progression from low adoption–low quality to high-quality, strategically embedded AI and associated outcomes.

Source: Authors, (2026).

Figure 5 illustrates how the structural model of AI integration in human resource processes translates into heterogeneous entrepreneurial and reputational outcomes across firms. Figure (a) illustrates that the color gradient is primarily aligned with the AI quality axis, indicating that predicted entrepreneurial achievement increases steeply as AI quality rises from low to high values, whereas variation along the adoption axis contributes only modest changes; this pattern is consistent with the model, where the estimated path coefficient from AI quality to entrepreneurial achievement was markedly larger than the coefficient from AI adoption. Figure (b) illustrates the compound effect of AI adoption and AI quality on predicted company reputation after propagation through entrepreneurial achievement, and the planar gradient suggests that reputational gains are most pronounced in regions with simultaneously high AI quality and at least moderate adoption, while regions with low quality remain associated with lower predicted reputation even when adoption is elevated. The data underlying these surfaces indicated that the indirect pathway AI adoption → AI quality → entrepreneurial achievement → company reputation accounted for a substantial share of the explained variance in reputation, whereas the direct path from adoption to reputation was weak and statistically non-significant, and these surfaces therefore visualise a mechanism in which the informational richness, reliability, and alignment of AI systems with HR decision processes control the efficiency of opportunity recognition and resource orchestration that define entrepreneurial performance [28].

Figure (c) illustrates the empirical distribution of firms across the AI adoption–quality plane and partitions them into four integration profiles; the quadrant-level means showed that early-stage adopters with low adoption and low quality recorded negative average entrepreneurial achievement and company reputation, symbolic adopters with high adoption but low quality improved slightly but remained below zero on both outcomes, selective high-performers with low adoption but high quality achieved positive average entrepreneurial achievement and near-neutral reputation, and strategic integrators with high adoption and high quality attained the highest mean entrepreneurial achievement and reputation values. These contrasts suggest that increases in adoption unaccompanied by quality improvements do not materially enhance firm-level performance, whereas even moderate adoption supported by high-quality AI infrastructure can strengthen the exploitation of HR data and thus entrepreneurial outcomes. Figure (d) illustrates a conceptual trajectory in which firms progress from low adoption–low quality through a purely symbolic adoption phase toward high-quality strategic integration that embeds AI into HR decision cycles; the upward arrow towards stronger entrepreneurial achievement and improved company reputation encapsulates that effective AI use emerges when system design, data integrity, and HR workflows are jointly optimized, and this pathway indicates that future interventions should target governance, training, and process redesign rather than technology volume alone [29].

IV. CONCLUSIONS

This work investigated the role of Artificial Intelligence integration in human resource practices of entrepreneurial firms in India, focusing on recruitment, development, and performance management. A survey design with SmartPLS structural equation modelling was used to examine relationships among AI adoption, AI quality, entrepreneurial achievement, and company reputation.

The measurement model demonstrated strong psychometric properties, with Cronbach's alpha values for all constructs exceeding 0.80, composite reliability coefficients approaching 0.90, and average variance extracted exceeding 0.72, and outer loadings ranging from 0.800 to 0.921. The structural model accounted for R^2 values of 0.592 for AI quality, 0.700 for entrepreneurial achievement, and 0.602 for company reputation, confirming substantial explanatory power for the specified pathways. Direct paths from AI adoption to entrepreneurial achievement and company reputation were small and statistically non-significant, while indirect effects through AI quality and entrepreneurial achievement were substantial. These patterns indicate that reputational benefits and entrepreneurial performance in AI-enabled HRM depend on the depth and quality of AI integration rather than nominal adoption. At the same time, the evidence suggests that high-quality AI systems in HR functions support innovation, operational efficiency, and a distinctive employer image in emerging economies. The study was constrained by its cross-sectional design, reliance on self-reported perceptions from HR professionals, and focus on large Indian entrepreneurial firms. Future work will extend this framework using longitudinal, multi-source data, will explore sectoral differences in AI-enabled HRM, and will identify specific AI capabilities, governance practices, and workforce skills that strengthen sustainable entrepreneurial outcomes and company reputation.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Nidhi Sonkar, Amit Kumar Pandey and Ratchagaraja Dhairiyasamy.

Methodology: Nidhi Sonkar and Amit Kumar Pandey.

Investigation: Nidhi Sonkar, Deekshant Varshney and Subhav Singh.

Discussion of results: Nidhi Sonkar, Ratchagaraja Dhairiyasamy and Deekshant Varshney.

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Supervision: Amit Kumar Pandey and Ratchagaraja Dhairiyasamy.

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VI. REFERENCES

- [1] Zhang J, Yuan Y. Multi-Dimensional Post Competency Evaluation Model in Human Resource Management under the Background of Artificial Intelligence. *Math Probl Eng* 2022;2022. <https://doi.org/10.1155/2022/9730127>.
- [2] Votto AM, Valecha R, Rad PN, Rao HR. Artificial Intelligence in Tactical Human Resource Management: A Systematic Literature Review. *International Journal of Information Management Data Insights* 2021;1. <https://doi.org/10.1016/j.jjime.2021.100047>.
- [3] Chilunjika A, Intauno K, Chilunjika SRT. Artificial intelligence and public sector human resource management in South Africa: Opportunities, challenges and prospects. *SA Journal of Human Resource Management* 2022;20. <https://doi.org/10.4102/sajhrm.v20i0.1972>.
- [4] Gélinas D, Sadreddin A, Vahidov RM. Artificial intelligence in human resources management: A review and research agenda. *Pacific Asia Journal of the Association for Information Systems* 2022;14:1–42. <https://doi.org/10.17705/1pais.14601>.
- [5] Weber P. Unrealistic Optimism Regarding Artificial Intelligence Opportunities in Human Resource Management. *International Journal of Knowledge Management* 2023;19:1–19. <https://doi.org/10.4018/IJKM.317217>.
- [6] Chowdhury S, Prasanta K, Dey PK, Joel-Edgar S, Bhattacharya S, Rodríguez-Espíndola O, Abadie A, et al. Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review* 2023;33. <https://doi.org/10.1016/j.hrmr.2022.100899>.
- [7] Rodgers W, Murray JM, Stefanidis A, Degbey WY, Tarba SY. An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. *Human Resource Management Review* 2023;33. <https://doi.org/10.1016/j.hrmr.2022.100925>.
- [8] Qahtani EHAL, Alsmairat MAK. Assisting artificial intelligence adoption drivers in human resources management: a mediation model. *Acta Logistica* 2023;10:141–50. <https://doi.org/10.22306/al.v10i1.371>.
- [9] Wuisan DSS, Sunarjo RA, Aini Q, Yusuf NA, Rahardja U. Integrating Artificial Intelligence in Human Resource Management: A SmartPLS Approach for Entrepreneurial Success. *APTISI Transactions on Technopreneurship* 2023;5:334–45. <https://doi.org/10.34306/att.v5i3.355>.
- [10] Sabale A, Subashini R. Enhancing HR Efficiency Through the Integration of Artificial Intelligence and Internet of Things: A Study on AI Implementation in Human Resource Management. *EAI Endorsed Transactions on Scalable Information Systems* 2024;11:1–11. <https://doi.org/10.4108/eetsis.4208>.
- [11] Band G, Bapat S, Sonkul D, Chavan N, Nandurkar PA, Ahmad MI. Assessing the Efficacy of Utilizing Artificial Intelligence for Human Resources Management in the Indian IT Industry. *Nanotechnol Percept* 2024;20:499–506. <https://doi.org/10.62441/nano-ntp.v20iS5.46>.
- [12] Amazian M, Nouria Z, Filali M. Human resources management in the age of artificial intelligence; Gestión de recursos humanos en la era de la inteligencia artificial. *Data and Metadata* 2024;3. <https://doi.org/10.56294/dm2024.347>.
- [13] Bouhsaien L, Azmani A. THE POTENTIAL OF ARTIFICIAL INTELLIGENCE IN HUMAN RESOURCE MANAGEMENT. *Applied Computer Science* 2024;20:153–70. <https://doi.org/10.35784/acs-2024-34>.
- [14] Korol E, Korol S. Governing the Commons through Rule Hybridity: Interactions Between Formal Institutions and Informal Norms in CPR Management. *Journal of Business and Management Studies* 2025;7:88–102. <https://doi.org/10.32996/JBMS.2025.7.4.4>.
- [15] Nawaz N, Arunachalam H, Pathi BK, Gajenderan V. The adoption of artificial intelligence in human resources management practices. *International Journal of Information Management Data Insights* 2024;4. <https://doi.org/10.1016/j.jjime.2023.100208>.

- [16] Korol E, Korol S. Bridging Theory and Practice: Applying Ostrom's Law to Real-World Resource Management. *Journal of Business and Management Studies* 2024;6:19–35. <https://doi.org/10.32996/JBMS.2024.6.6.2>.
- [17] Yamin MAY, Almuteri SD, Bogari KJ, Ashi AK. The Influence of Strategic Human Resource Management and Artificial Intelligence in Determining Supply Chain Agility and Supply Chain Resilience. *Sustainability (Switzerland)* 2024;16. <https://doi.org/10.3390/su16072688>.
- [18] Korol E, Korol S. AI, Legal Pluralism, and Property Governance: Comparative Insights on Rulemaking and Enforcement from the U.S., U.K., Ukraine, China, and India. *Journal of Business and Management Studies* 2025;7:182–93. <https://doi.org/10.32996/JBMS.2025.7.4.10>.
- [19] Wijaya EFA, Qamari IN. Analysis of Research on Artificial Intelligence in Human Resources Management: A Bibliometric Analysis. *International Research Journal of Multidisciplinary Scope* 2024;5:108–21. <https://doi.org/10.47857/irjms.2024.v05i02.0383>.
- [20] Cai F, Zhang J, Zhang L. The Impact of Artificial Intelligence Replacing Humans in Making Human Resource Management Decisions on Fairness: A Case of Resume Screening. *Sustainability (Switzerland)* 2024;16. <https://doi.org/10.3390/su16093840>.
- [21] Dong J, Yan S, Yang X. Influencing Factors and Mechanisms of Value Co-Creation in Artificial Intelligence-Driven Human Resource Management: A System Dynamics Simulation. *Systems* 2024;12. <https://doi.org/10.3390/systems12090352>.
- [22] Korol E, Korol S. AI-Augmented Commons Governance: Ethical Rulemaking and Enforcement for Sustainable Resource Management in Rural Areas. *Journal of Business and Management Studies* 2025;7:09–25. <https://doi.org/10.32996/JBMS.2025.7.5.2>.
- [23] Chowdhury S, Budhwar PS, Wood GT. Generative Artificial Intelligence in Business: Towards a Strategic Human Resource Management Framework. *British Journal of Management* 2024;35:1680–91. <https://doi.org/10.1111/1467-8551.12824>.
- [24] Capasso M, Arora P, Sharma D, Tacconi C. On the Right to Work in the Age of Artificial Intelligence: Ethical Safeguards in Algorithmic Human Resource Management. *Business and Human Rights Journal* 2024;9:346–60. <https://doi.org/10.1017/bhj.2024.26>.
- [25] Koprulu F, Öznacar B, Öznacar M, Yeboah SO. Artificial Intelligence in the Management of Human Resources and Psychology; İnsan Kaynakları ve Psikoloji Yönetiminde Yapay Zeka. *Cyprus Turkish Journal of Psychiatry and Psychology* 2024;6:346–53. <https://doi.org/10.35365/ctjpp.24.4.07>.
- [26] Choudhari Y, Shrestha P, Singh G, Bindra S. The Impact of Artificial Intelligence (AI) on Talent Acquisition in Human Resource Management. *Australasian Accounting, Business and Finance Journal* 2025;19:153–72. <https://doi.org/10.14453/aabfj.v19i1.09>.
- [27] Pedrami M, Vaezi SK. Factors influencing artificial intelligence adoption in human resource management: a meta-synthesis and systematic review of multidimensional considerations. *Journal of Work-Applied Management* 2025. <https://doi.org/10.1108/JWAM-10-2024-0158>.
- [28] Wang B. Artificial intelligence and deep learning in human resource management: tools techniques and research challenges. *International Journal of Information and Communication Technology* 2025;26:99–111. <https://doi.org/10.1504/IJICT.2025.146810>.
- [29] Wang N, Zhang X, Li S, Gao X. Applications of Artificial Intelligence in Enterprise Human Resource Management. *Information Resources Management Journal* 2025;38. <https://doi.org/10.4018/IRMJ.389707>.