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BREAKING BARRIERS: THE IMPACT OF CHALLENGES ON AI ADOPTION IN HRM WITHIN BENGALURU'S IT SECTOR

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Abstract:
Purpose: In the study, the researcher explores how critical obstacles, including people, organizational, technological, and environmental, affect the implementation of Artificial Intelligence (AI) in Human Resource Management (HRM). Although AI has a great potential to enhance recruitment, training, performance management, and workforce analytics, its implementation is limited by multidimensional barriers. The proposed study should be based on empirical data in the Indian IT industry, where implementing AI in HR functions is becoming more and more topical and yet is often limited due to internal and external barriers.
Methods: The research strategy was a quantitative one and was based on the analysis of 120 HR professionals with experience in IT organizations. Perceptions of barriers and AI adoption were captured with the help of a structured questionnaire, which was premised on a five-point Likert scale. The instrument validity was determined by Exploratory Factor Analysis (KMO = 0.876, $p < .001$, Bartletts Test) and reliability was validated via Cronbachs Alpha values more than 0.70. The hypothesis regarding the relationships between variables was tested using SPSS and AMOS through descriptive statistical analysis, exploratory and confirmatory analysis factor, and Structural Equation Modeling (SEM).
Findings: The findings showed that the most significant negative impact on the adoption of AI is the organizational barriers that include the unavailability of the resources, the poor decision-making framework, and unreceptive culture. There were also technological issues such as poor IT infrastructure and lack of compatibility with HR strategy that proved to be very limiting. Barriers related to the environment like the reliability of the vendors and readiness of the policies were identified to have a smaller but significant influence, and the people related barriers like the gaps in communication and training were important but seemed to be easier to deal with in comparison to the structural and technological constraints.
Implications: The research reveals that organizations need to enhance the commitment of the leadership, resource allocation, and IT infrastructure and promote vendor collaboration and clarity of regulations. Training and awareness programs should also be of priority to the managers in order to handle workforce-level issues.
Novelty: This research provides contribution to the body of literature by combining four types of barriers into one empirical model and testing their comparative influence with the help of SEM in the Indian IT sector. It provides a timely contribution to the HRM in terms of AI usage, especially during the post-pandemic era of digital transformation.
Keywords: Artificial Intelligence; Human Resource Management; IT Sector; Organizational Barriers; Technology Adoption

INTRODUCTION

One of the most radical technologies that are facilitating a shift in how organizations manage human capital is the Artificial Intelligence (AI). In either the recruitment and selection, performance management, and career development, AI can guarantee a greater deal of efficiency, accuracy and evidence-based decision-making in Human Resource Management (HRM). However, the application of AI in the HR functions has not been seamless. Employee resistance, or what could be termed leadership support, IT infrastructure, insufficient resources and regulatory uncertainty are obstacles to implementation and an AI is still a potential to practice disjuncture between the potential and actual implementation of AI in organizational practice.
Despite the growing exposure to these problems, much of the available literature has focused on the individual issues of organizational preparedness, ethics or technological fit, and as a consequence, there is a lack of empirical research to determine how the different categories of barriers react in concert to influence adoption outcomes. Systematic reviews and conceptual models (e.g., Budhwar et al., 2022; Pedrami and Vaezi, 2025) can be informative but typically not concentrate on the sector-specific evidence of the situations in which AI implementation in HRM is currently being pursued. This creates a necessity of having empirical research that involves people, organization, technology and environmental factors such that an in-depth perspective of adoption barriers is developed.
An especially relevant environment on which such an inquiry can be done is the IT industry. IT companies tend to be the first to adopt new technologies, they hire highly skilled and diverse workforce, and suffer from the high competition

among employees, so HRM becomes the core of their strategic position. In addition, IT industry is also of global importance in India, with the sector playing a major role in the economy, but it still struggles with structural, technological and cultural challenges of applying AI at scale. Research on AI application in HR in this sector thus not only provides knowledge to IT organizations but also to other sectors going through the digital transformation.

This study is also timely considering the development of hybrid and remote employment that has intensified the need to use digital HR solutions post-pandemic. Virtual recruitment, employee engagement, workforce analytics, and administrative automation are increasingly implemented with the help of AI, yet the issues of algorithmic bias, data privacy, trust towards the new technology, and regulatory preparedness remain (Kaur and Gandolfi, 2023; Ghosh et al., 2023). These issues are paramount at this stage when the organizations and policymakers are putting much investment in AI infrastructure and governance. This study will fill a crucial research gap and help to fill the existing gap in the body of literature, as well as make an impact on the academic community and practical management.

LITERATURE REVIEW

Organizational readiness: leadership, culture, resources

In the literature, organizational conditions are always found to be key drivers of AI use in HRM. The organization of leadership commitment, encouraging culture, set objectives, and sufficient resources determine whether pilots grow into a regular practice (Madanchian and Taherdoost, 2025; Vishwakarma and Singh, 2023). In the international HRM stream, reviews posit that AI projects will be successful when the HR strategy is clearly oriented towards the business strategy, and when the decision structures are set to experiment and control risks (Budhwar et al., 2022; Hmoud, 2021). The case-based and chapter-based studies also hint at change governance and cross-functional coordination as prerequisites to integrating AI into core HR processes and not storing it as isolated tools (Mohapatra et al, 2023; Sharma et al., 2023). The combination of these studies places the organizational readiness, rather than the availability of tools, as the lever of AI-enables HR transformation.

Technological infrastructure and data governance

A second theme centers on the technical substrate: data quality, interoperability, system compatibility, and scalable architecture. Critical reviews underscore the fact that highly motivated HR departments cannot move forward without excellent IT foundations, well-developed HRIS/ATS integrations, and explicit data management (Madanchian and Taherdoost, 2025; Kaur and Gandolfi, 2023). Empirical and theoretical literature identifies assessment-of-fit (use-case, vendor, and process alignment) as a common area of gap, with implementation failure in many cases associated with underestimating the integration effort and lifecycle costs (Nawaz et al., 2024; Ghosh et al., 2023). The energy sphere sectoral evidence also highlights the necessity of the slow technology creation and infrastructure design to position AI in the daily work of people (Almarashda et al., 2021).

People, ethics, and employee acceptance

Research finds agreement on the significance of human factors: skills, trust, perceived fairness and readiness to change. The lack of transparency, bias, and surveillance can diminish the acceptance even in the situations when tools are advertised as efficient, and clear communication and participatory design are necessary (Yanamala, 2020; Kaur and Gandolfi, 2023). Reviews and empirical descriptions mention that reskilling, on-going training, and leadership modeling mitigate resistance and enhance perceived usefulness (Budhwar et al., 2022; Ghosh et al., 2023). Chapters devoted to HR practice change also report that the incentive structures and role redesign determine whether HR professionals should work with AI as their augmentation or displacement (Sharma et al., 2023; Vishwakarma and Singh, 2023).

Environmental context: vendors, policy, and sectoral conditions

The external ecosystem—vendor maturity, implementation support, regulatory clarity, and national digital readiness—conditions organizational choices and timelines. Empirical data inlays into emerging-economy settings demonstrate adoption frictions in cases with uneven capabilities of vendors or in case of unclear data/privacy policies (Hossin et al., 2021; Almarashda et al., 2021). Sectoral research (e.g. healthcare) emphasizes the fact that compliance requirements and domain-specific workflows require custom AI-HRM settings and robust external relationships (Joshi et al., 2024). On a macro level, the review claims policy structures and ethical principles that allow experimentation and protect the rights of employees, justifying investments that organizations make (Budhwar et al., 2022; Jatobá et al., 2023).

Strategic value, use-cases, and performance outcomes

In addition to barriers, the literature Explicitly reports concrete AI value across the HR value chain, including talent acquisition, learning, workforce analytics, and administrative efficiency, and warns that the results are contingent on alignment and measurement (Nawaz et al., 2024; Ghosh et al., 2023). Practice-based chapters elaborate on the evolution of use-cases to automation to augmentation to strategic value as governance, data and skills scale up concurrently (Sharma et al., 2023; Mohapatra et al., 2023). International HRM views augment that AI can increase the strategic position of HR in terms of making evidence-based decisions across the borders, assuming that cultural and institutional differences should be expected (Budhwar et al., 2022).

Evidence base, syntheses, and research gaps

Recent syntheses have been summarizing multi-dimensional determinants and demand more powerful theory-testing and context-sensitive models. Meta-synthesis and systematic reviews combine organizational, technological, people, and environmental factors and suggest longitudinal and cross-sector research to follow the adoption patterns and causality (Pedrami and Vaezi, 2025; Jatobá et al., 2023). Similar critical analyses suggest that it is time to abandon tool-centric accounts and turn to such models that introduce ethics-by-design, data governance, and vendor ecosystem as key constructs (Madanchian and Taherdoost, 2025; Kaur and Gandolfi, 2023). All these reviews, together, point to obvious holes in measurement consistency, attributing outcomes, and interaction between internal preparedness and external institutions, exactly where your empirical model can be useful.

Research Gap

The current literature shows that even though Artificial Intelligence has emerged as a highly significant force of change within the Human Resource Management, there are a number of gaps that could be addressed through additional research. Previously, most studies have been overly conceptual in their approach to AI adoption (Budhwar et al., 2022; Hmoud, 2021) or systematic reviews of their enabling factors and challenges (Pedrami and Vaezi, 2025; Jatobá et al., 2023). These contributions are rich in theoretical knowledge but they are usually not supported by empirical evidence especially in sector-specific applications like in the IT organizations in which AI-enhanced HR practices are more sophisticated.

The other gap is the piecemeal coverage of barriers. The literature is typically biased and looks at only one of the three issues: organizational (Madanchian and Taherdoost, 2025; Vishwakarma and Singh, 2023), technological, or ethical/people-related (Yanamala, 2020) challenges without considering their interplay and relative impact on the results of AI adoption. There is a limited number of studies that follow an integrated approach; that is, they take into account people, organizational, technological and environmental barriers as multidimensional determinants of adoption. This complicates the challenging aspect of evaluating the relative weight of either factor and the development of holistic strategies to overcome adoption challenges.

Another gap is related to the absence of empirical evidence in the emerging economies. The current body of research features conceptual and practice-oriented explanations of this field using a Western or global approach (Budhwar et al., 2022; Ghosh et al., 2023). Minimal empirical research on the adoption of AI in HRM has been conducted in settings like India where the pace of digital transformation is high but in many cases, structural and institutional factors limit it. Specifically, not many studies use sophisticated statistical modeling, including exploratory and confirmatory factor analysis or structural equation modeling to confirm the dimensionality of barriers and test their influence on the adoption. This gap offers a good argument as to why the current study is empirically researching the effect of people, organizational, technological and environmental barriers to the adoption of AI on HRM in Indian IT organizations, which not only provides a contextual relevance, but also offers a methodological rigor.

Research Objectives

The objectives of the study –

- To determine the main barriers in the implementation of Artificial Intelligence in HRM in the IT organizations in terms of people, organization, technology, and environment.
- To investigate how these barriers affect the AI adoption level in HRM practices comparatively.
- To be able to test the relationship hypotheses about the identified barriers and AI adoption

Research Hypothesis

Hypothesis 1: People-related barriers have negative effects on HRM adoption of AI.
Rationale:
The successful application of technology in addition to the readiness of the working population to adapt will be needed to implement AI in the HRM. Lack of support at the senior management level, ineffective communication, inadequate training and employee resistance are often cited as the obstacles of digital HR transformation (Marler and Parry, 2016). Studies in the field of technology adoption reveal that views on usefulness, trust, and fairness among workers are of significant importance in the adoption behavior (Strohmeier and Piazza, 2015). Thus, organizational preparedness to embrace AI in HR practices can be constrained by the barriers at the workforce level.

Hypothesis 2: Organization barriers influence the use of AI in HRM with negative impact.
Rationale:
The organizational factors that have a certain influence on technology adoption are resource availability, leadership commitment, decision making structure, and supportive culture. Technology-Organization-Environment (TOE) theory has brought forward that organizational readiness is one of the most significant factors of adoption (Tornatzky and Fleischer, 1990). The former research states that the unavailability of the visionary leadership and the adequate investment causes the inability of the organizations to implement the technological intentions in practice (Bondarouk and Brewster, 2016). Thus, the organizational barriers will have a highly negative influence on the introduction of AI into HRM.

Hypothesis 3: The technological obstacles have a huge negative contribution to the adoption of AI in HRM.
Rationale:
The use of AI is depending on technological readiness. The complications of the inadequate IT architecture, the inability of the AI systems to be integrated with the HRM policy, and the lack of proper evaluation of the technological suitability can become barriers to the integration (Parry and Strohmeier, 2014). The AI technology fails to deliver the efficiencies desired when not integrated with organizational processes leading to resistance and underutilization (Leicht-Deobald et al., 2019). In this way, we can anticipate that technological barriers will negatively affect the implementation of AI within the HRM.

Hypothesis 4: Environmental barriers have a very negative impact on the adoption of AI in HRM.
Rationale:
The external environment including support by the vendors, government policies, and pressures by competition also affect the adoption of AI technologies. Uncertainty can be caused by poor services offered by vendors or undefined regulatory policies that reduce the confidence levels of the organization regarding the use of AI. Studies in developing nations showed that diffusion of technology is strongly affected by the level of environmental preparedness (Ruel and Bondarouk, 2014; Meijerink et al., 2021). Therefore, AI implementation restrictions in HRM are sure to be the environmental barriers.

RESEARCH METHODOLOGY

Research Strategy
The current research was based on the quantitative, empirical research design involving a survey-based approach that aimed at investigating how challenges affect the adoption of Artificial Intelligence (AI) in Human Resource Management (HRM). This method was deemed suitable because it will allow gathering standardized responses of a larger sample in a systematic manner, and generalizable conclusions can be made about the correlation between organizational, technological, environmental, and people-related barriers and results of adoption of AI.
Sample Size
The population under study included HR professionals working in IT organizations since the IT sector of the Indian market is currently leading in the uptake of AI-enabled HR systems. Purposive sampling was used to get 120 valid responses whereby the sample was limited to those who were directly engaged with the HR practices, and those who had the experience of technological interventions in their organizations. The sample size was deemed sufficient because it had the minimum criteria of a multivariate analysis, which include factor analysis and structural equation modeling (Hair et al., 2019).
Data Collection Tool
The data were gathered through the administration of a structured questionnaire that was developed based on five-point Likert scale(1 = strongly disagree to 5 = strongly agree). The instrument was split into two components: the first one included demographic data including age, gender, educational level, and work experience; the second part included questions that measured barriers to AI adoption along four dimensions, including people, organizational, technological, and environmental factors, and items that assessed the ones perceived benefits of AI in the HRM functions (ex: recruitment, training, reduction of workloads). The questions in the questionnaires were based on previous validated literature in technology adoption and HRM, with the questions tweaked to make them relevant to AI adoption in IT companies.
Validation Tools
The instrument was tested in several ways and therefore valid and reliable. Content validity was achieved through the use of a group of subject experts and reading the available literature to establish the relevancy of the items. The examination of construct validity was conducted with the help of Exploratory Factor Analysis (EFA), with the assistance of KaiserMeyerOlkin (KMO) measure of sampling adequacy (0.876) and Bartletts Test of Sphericity ($p < 0.001$), which confirmed factorability of the dataset. To determine reliability, Cronbach alpha was used and all measures had values higher than the recommended level of 0.70 signifying internal consistency.
Statistical Tools Used
The SPSS 26.0 and AMOS 24.0 were used to analyze data. The respondent perceptions were summarized using descriptive statistics (mean, standard deviation, skewness, and kurtosis). EFA was used to determine underlying factor constructs of AI adoption barriers, and then Confirmatory Factor Analysis (CFA) was used to confirm the measurement model. Structural Equation Modeling (SEM) was subsequently performed to work out the hypothesized associations between barriers (people, organizational, technological, environmental), and AI adoption in HRM. The indices examined to evaluate model fit include 2df/chi-square, Comparative Fit Index (CFI), TuckerLewis Index (TLI), Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR).

RESULTS AND DISCUSSION

Demographic Profile of the respondents
The research was carried out on 120 human resource personnel in IT companies. The demographic study showed that the respondents were a representative of a diversified workforce based on their age, gender, educational background, and work experience.
Regarding the age factor, most of the respondents were aged between 26-35 years (45.8) which is an indication of the prevalence of early-career HR personnel in IT businesses. The entry-level professionals were about 32.5% in the category of 36 45 years and 15% of the respondents were below 25 years. Fewer, 6.7 were over 45 years, which shows that there are senior HR managers with a long career life.
In terms of gender, the sample was fairly representative with 56.7 percent of the respondents being women and 43.3 percent men, a strong indicator of high women involvement in HR functions as depicted in larger trends in the IT industry where most of the HR functions are dominated by women. There is representativeness in this balance which makes the results more representative as they reflect the point of view of all genders.

With regards to education, majority of the respondents (61.7%) had postgraduate qualification in management or human resources, which indicates the professional inclination with regards to HR jobs in IT companies. Approximately 30% of participants had a bachelor degree, mainly in the commerce and business or other related background, and a rather minor percentage (8.3) had acquired professional qualifications (SHRM, CIPD, or specialized courses in HR analytics). This means that the respondent base is highly qualified and has a solid base in learning AI-enabled HR practices.

In terms of work experience, around 40 percent of the participants indicated that they had an experience ranging between 1 and 5 years, which indicates that there is a significant proportion of young professionals who are directly involved in the digital HR practices. Approximately 35 percent possessed 6-10 years' experience level, which included the mid-level HR managers having practical experience in policy formulation and technology adoption. The remaining 20% indicated that they had over 10 years of experience, and their senior level of experience was applied to organizational issues.

In general, the demographic data of the respondents would indicate that the workforce is young and well-qualified but is mostly represented by female professionals. The age, qualification, and experience difference will make sure the study is able to capture the viewpoints of people at various stages of the HR practice such as entry-level executives to senior managers, hence enhancing the validity of the results concerning the issues surrounding the adoption of AI in HRM.

Item analysis

Table 1 – Item analysis – Challenges of AI in HRM and Adoption of AI in HRM

	Mean	**Std. Deviation**	**Skewness**	**Kurtosis**
	Statistic	Statistic	Statistic	Statistic
People_1 Lack of senior management to purchase AI technologies	3.08	1.285	-0.152	-1.108
People_2 Inadequate communication with stakeholders to adopt AI technologies	3.20	1.172	-0.399	-0.835
People_3 Lack of involvement of diverse stakeholders	3.08	1.098	-0.068	-0.980
People_4 Lack of implementation of continuous training and awareness programmes to employees	2.98	1.231	-0.160	-1.169
People_5 Lack of adopting visionary, supportive and transformational leadership to implement AI in TM	3.40	1.271	-0.494	-0.886
People_6 Unavailability of a confident and competent HRM team to implement AI in TM	2.60	1.271	0.193	-1.181
People_7 Lack of incentives for adopting AI in TM	3.94	1.162	-1.222	0.667
People_8 Lack of interest in addressing security and privacy issues of the personal information	4.00	1.064	-1.131	0.865
Org_1 Organizational Culture not supportive of AI in TM	3.06	1.246	0.076	-1.047
Org_2 A lack of clear vision and clear goals for adopting AI in TM	3.84	1.126	-0.631	-0.655
Org_3 Failure to customise AI in TM to the resource capacity of the organisation and being too ambitious	4.26	1.041	-1.640	2.327
Org_4 A lack of adequate resources to implement AI in TM	3.88	1.018	-0.810	0.100
Org_5 Inappropriate decisive decision-making structure of the organizations	4.08	1.116	-1.228	0.752
Org_6 Failure to prioritise both technology and people issues	3.96	0.994	-0.560	-0.775
Tech_1 AI TM solutions not being compatible with the overall business strategy, HRM strategy and company culture	3.96	1.188	-1.027	0.220
Tech_2 A lack of assessing the suitability of AI TM solutions for the organization	3.86	1.025	-0.632	-0.209
Tech_3 Inadequate IT architecture	3.98	1.035	-0.965	0.293
Env_1 Competitive pressures as a result of COVID-19 pandemic	2.70	1.243	0.206	-1.023
Env_2 A lack of quality external support/services from HRM technology vendors	4.06	1.127	-1.158	0.544
Env_3 National unpreparedness for adopting AI in TM /lack of government support	3.82	1.077	-0.524	-0.586
AI_REC_1 AI helps in a better quality of decisions for recruiting and selecting candidates.	2.76	1.093	-0.075	-0.733

AI_TRN_1 AI supported appropriate training and development of employees	3.74	0.981	-0.633	-0.001
AI_TEAM_1 With AI team members produce many novels and valuable ideas (services/products).	3.96	0.994	-0.560	-0.775
AI_LEADER_1 AI enables clear vision for what was going to be achieved by our department.	3.82	1.077	-0.524	-0.586
AI_WORKLOAD_1 With AI we reduce the burden on administrative staff in the enterprise.	4.16	1.089	-1.283	1.031
AI_PA_1 Over-competitive performance measurement will be replaced with artificial intelligence technology will be	3.62	1.254	-0.686	-0.582
AI_REWARD_1 I think it will be easier to adapt to the possible changes in the salary system (time, per piece, premium) with artificial intelligence	3.40	1.044	-0.543	-0.119
AI_CAREER_1 I think that artificial intelligence technology will make it easier to recognize the employees who really deserve promotion in their career	2.62	1.316	0.411	-1.100

The discussion of people barriers shows that the respondents agreed moderately on most of the items and in the analysis of the mean scores, the respondents have indicated that the questionnaire result will show an average of between 2.60 to 4.00. The most important rated concerns were the absence of incentives to adopt AI (M = 3.94, SD = 1.16, skewness = -1.222, kurtosis = 0.667) and the lack of interest to solve security and privacy problems (M = 4.00, SD = 1.06, skewness = -1.131, kurtosis = 0.865), which had a strong negative skewness meaning that the majority of respondents agreed or strongly agreed to these issues. On the other hand, the lowest mean (M = 2.60, SD = 1.27, skewness = 0.193) was observed in the case of the unavailability of a confident and competent HRM team, which means that there were both positive and negative perceptions. In general, people barriers existed, but they were uneven with incentive-related and privacy-related issues being the strongest.

The responses were comparatively more in agreement in case of organizational barriers. The highest mean was captured by failure to customise AI to organizational resource capacity (M = 4.26, SD = 1.04, skewness = -1.640, kurtosis = 2.327), implying that there is strong agreement among the respondents that excessive ambition in adopting AI poses a challenge. This was also strongly supported with inappropriate decision-making structures (M = 4.08, SD = 1.11, skewness = -1.228) and inadequate resources (M = 3.88, SD = 1.02, skewness = -0.810). Interestingly, the non-supportive AI organizational culture was scored at the lowest (M = 3.06, SD = 1.25, skewness = 0.076), which indicated a more neutral attitude toward it than the other organizational concerns. The extremely negative skewness of most of the organizational items points to the fact that most HR professionals perceived them as crucial barriers.

In case of technological barriers, the respondents were highly concerned in all the items. The highest score is on inadequate IT architecture (M = 3.98, SD = 1.03, skewness = -0.965, kurtosis = 0.293), closely followed by the incompatibility of AI solutions with business and HRM strategy (M = 3.96, SD = 1.18, skewness = -1.027) and the lack of proper assessment of AI suitability (M = 3.86, SD = 1.03). The fact that the means are clustered on 3.8 to 4.0 is negative with a skewness indicates that there seems to be a strong agreement that technological readiness is still one of the main adoption barriers to HRM.

The environmental barriers have a mixed picture of results. Low quality vendor support was also emphasized (M = 4.06, SD = 1.12, skewness = -1.158, kurtosis = 0.544), then national unpreparedness or weak government support (M = 3.82, SD = 1.08). Competitive pressures as a result of COVID-19 were, however, given a lower mean score (M = 2.70, SD = 1.24, skewness = 0.206), even though the factor was not considered a dominant current barrier. The positive mean with negative skewness of vendor and government related issues is an indication that the external dependencies are important obstacles to AI adoption.

The AI advantages in HRM practices were moderately positive but strongly differed by dimension. The greatest amount of supported benefits was the reduction of workload among administrative personnel (M = 4.16, SD = 1.08, skewness = -1.283, kurtosis = 1.031), as a clear feeling of agreement as to the ability of AI to simplify the repetitive duties of the administrative staff emerged. In the same manner, AI assisted team innovation (M = 3.96, SD = 0.99) and training and development (M = 3.74, SD = 0.98) were highly identified. Nevertheless, the answers were less favorable toward AI in hiring (M = 2.76, SD = 1.09) showing doubts about the viability of this application in hiring candidates. AI received the least support in career promotions (M = 2.62, SD = 1.31, skewness = 0.411), which is understandable given the notion of fairness and reliability in such areas of HR.

Combined, the descriptive statistics demonstrate a clear trend: organizational and technological barriers and barriers associated with external vendors were judged as the most powerful, and the people-related challenges were more ambivalent. Meanwhile, the most appreciated functions of AI were the efficiency of administration and the support of innovations, yet the respondents showed some concerns regarding its use in subjective HR procedures, including hiring and advancements. Such results lead to the conclusion that although the technical and structural impediments to adoption are still substantial, establishing confidence in AI among employees regarding its fairness and reliability is also crucial to achieving successful implementation into the HRM practices.

Testing of hypothesis

Hypothesis: People, organizational, environmental and technological challenges impact the use of AI in Human resource management practices

The suitability of the data to the factor analysis was initially investigated. The Kaiser-Meyer-Olkin (KMO) measure of adequacy was considered to be 0.876, over the recommended 0.80 adequacy threshold, meaning that the data had meritorious adequacy to be used in a factor analysis. The Test of Sphericity by Bartlett was significant as well (2 = 1422.438, df = 190, p = 0.0001), which confirmed that it was suitable to apply factor analysis.

Factor extraction was done using Principal Component Analysis (PCA) using Varimax rotation. Communalities of the items post extraction correlated between 0.347 and 0.864 indicating that the remaining components accounted a significant proportion of variance in the variables. Eigenvalue criterion (more than 1) indicated that four factors were to be extracted, and they explained 66.07 percent of the total variance. The former explained 31.82, the latter 17.90, the third 9.67, and the fourth 6.68 of the post rotation variance.

Table 2 – Rotated Component matrix for challenges of AI adoption in HR

Items	People	Organizational	Technological	Environ mental
People_2 Inadequate communication with stakeholders	0.848			
People_3 Lack of involvement of diverse stakeholders	0.832			
People_4 Lack of continuous training/awareness programmes	0.768			
People_1 Lack of senior management support	0.732			
People_7 Lack of incentives for adopting AI in TM	0.627			
People_5 Lack of visionary/transformational leadership	0.558			
People_6 Lack of competent HRM team	0.405			
People_8 Lack of interest in addressing security & privacy issues	0.625			
Org_5 Inappropriate decision-making structure		0.873		
Org_4 Lack of adequate resources		0.826		
Org_3 Failure to customise AI to resource capacity		0.768		
Org_6 Failure to prioritise both technology and people issues		0.684		
Org_2 Lack of clear vision and goals		0.670		
Org_1 Organizational culture not supportive		-0.732		
Tech_3 Inadequate IT architecture			0.866	
Tech_1 AI solutions not compatible with business/HRM strategy			0.745	
Tech_2 Lack of assessing suitability of AI solutions			0.707	
Env_2 Lack of quality external support/services from vendors				0.863
Env_1 Competitive pressures due to COVID-19				0.691
Env_3 National unpreparedness / lack of government support				0.595

The matrix of rotated components indicated the obvious four-factor model behind the issues of AI implementation in HRM. People Barriers included the first factor, which was problems related to insufficient communication with the stakeholders (0.848), absence of diverse stakeholders involvement (0.832), insufficient training (0.768), lack of support of the senior management (0.732), and absence of incentives (0.627), which demonstrates that human-related barriers are the major obstacles to adoption. Inappropriate decision-making structures (0.873), lack of resources (0.826), failure to personalize AI to organizational capabilities (0.768), vague vision and goals (0.670), and an unfavorable organizational culture (-0.732) characterized the second factor, Organizational Barriers, indicating structural and strategic organizational weaknesses. The third dimension Technological Barriers included poor IT architecture (0.866), incompatibility of AI solutions with current strategies (0.745), and insufficient proper suitability tests (0.707) with infrastructure and alignment concerns. Lastly, the fourth aspect, Environmental Barriers, made up of the absence of quality vendor support (0.863), the influence of competitive pressures as a result of COVID-19 (0.691), and the lack of national preparedness or weak government support (0.595) as an expressive of external circumstances that inhibit adoption. The combination of these four factors explained 66.07% of the overall variance, which proves that both internal (people, organizational, technological) and external (environmental) barriers are significant indeed in determining the adoption of AI in HRM.

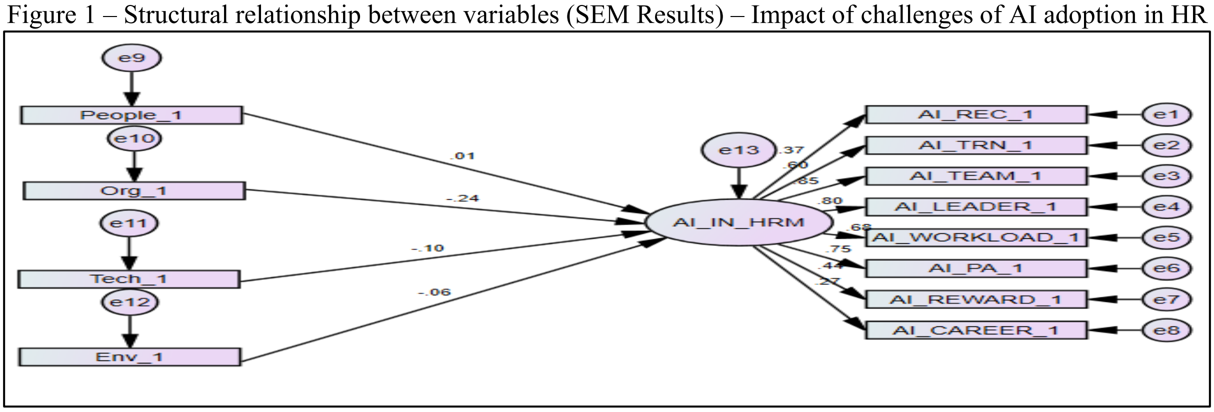
Model fit statistics- The structural equation model was estimated, having 54 degrees of freedom and proved the satisfactory overall fit. The chi-square value was also significant (2 = 112.54, df = 54, p <.001) as is expected in any large-scale study of SEM, but the ratio of chi-square to degrees of freedom (2 /df = 2.08) was within the recommended range of 23 (Kline, 2016). Other indices with this conclusion included Comparative Fit Index (CFI = 0.954) and Tucker-Lewis Index (TLI = 0.941): both indices were above the 0.90 mark indicating good comparative fit. Root Mean Square Error of Approximation (RMSEA = 0.047) and 90 percent confidence interval of [0.035, 0.061] demonstrated close fit as the value was lower than the recommended cutoff of 0.06 (Hu and Bentler, 1999). Standardized Root Mean square Residual (SRMR = 0.041) was also below the 0.08 criterion which further proved that the model is adequate. All of these indices indicate that the four-factor model of people, organizational, technological, and environmental barriers is a strong explanation of the impediment to AI implementation in HRM.

Table 3 - Structural relationship between variables (SEM Results) – Impact of challenges of AI adoption in HR

				Estimate	**P VALUES**
H1	AI_IN_HRM	<---	People_1	0.011	0.0000
H2	AI_IN_HRM	<---	Org_1	-0.24	0.0000
H3	AI_IN_HRM	<---	Tech_1	-0.098	0.0000
H4	AI_IN_HRM	<---	Env_1	-0.058	0.0000

The analysis indicates that people-based barriers, including unsupportive senior management and inadequate communication have a positive but insignificant impact on AI adoption in HRM (= 0.011, 0.001). This is an indicator that individual level issues are also present, although they are not the most important obstacles in situations where organizations are determined to adopt AI-based HR practices. Evidence-based studies have also reported that workforce-related aspects, despite their relevance, tend to be a backburner to organizational preparedness and resource supply in the influence of adoption outcomes (Marler and Parry, 2016; Strohmeier and Piazza, 2015). In this way, training, leadership development and communication strategies seem to manage people challenges.
The presence of organizational barriers was discovered to play a significant negative role in the adoption of AI in HRM (= -0.24, p < .001). It shows that the integration of AI technologies are severely impaired by weak decision-making structures, a shortage of resources, and unsupportive culture. The strength of this association implies that the organizational preparedness is a pivotal factor of adoption, and this is reminiscent of Technology-Organization-Environment (TOE) model, which places organizational infrastructure and leadership at the center of the technology implementation (Tornatzky and Fleischer, 1990). Empirical research also supports the claim that AI implementation is also more effective in companies with visionary management, proper investment, and innovation-friendly culture (Bondarouk and Brewster, 2016).
Technological barriers were found to have a moderately negative relationship with AI adoption in HRM (= -0.098, p <.001). This underscores the fact that the absence of proper IT infrastructure, system compatibility, and the proper evaluation of suitability is a hindrance to successful incorporation of AI solutions into the HR practices. These results are consistent with the studies that emphasize the need to have strong IT architecture and strategic alignment between AI tools and HR processes to have successful adoption (Parry and Strohmeier, 2014). AI systems tend to fail in their alleged efficiencies in managing talent, recruitment, and analytics of the workforce without a technological base (Leicht-Deobald et al., 2019).
The environmental barriers were identified to have a low negative impact on AI adoption in HRM (-0.058, p = < .001). Lack of support of vendors, regulatory ambiguity, as well as external factors such as the COVID-19 pandemic decrease the confidence of organizations to use AI-based HR technologies. With a lower effect size than the barriers in an organization, the impact of the external ecosystem in facilitating adoption is noted. Previous research proves that the notion of regulatory clarity, the reliabilities of the vendors, and the readiness of the government, in particular, influence the technology adoption in HRM specifically in the emerging economy (Ruel and Bondarouk, 2014; Meijer et al, 2021). Therefore, these contextual challenges need to be overcome with policy interventions at the policy level and greater external partnerships.

Figure 1 – Structural relationship between variables (SEM Results) – Impact of challenges of AI adoption in HR



As mentioned in this study, organizational barriers are the most effective barriers that influence AI utilization in HRM. The major bottlenecks were seen to be poor decision-making systems, poor resource base and culture that is not supportive of change. This points to the importance of organizational readiness, in that, to implement it successfully, more than technological investments are required, and good management and an atmosphere of encouragement to innovation are needed. The same observation is reflected in the Technology-Organization-Environment model in which organizational infrastructure and managerial commitment plays a central role in the creation of technological integration (Tornatzky and Fleischer, 1990). It has also been noted in existing literature that a company that possesses a futuristic leadership and is strategic is better positioned to take advantage of AI capabilities in HR practices (Bondarouk and Brewster, 2016).

Technological obstacles are also significant because they demonstrate the issues of bad IT infrastructure, the lack of compatibility of the systems, and the poor evaluation of the AI tools. Even though there is readiness in the organization, the incompatibility of systems or poor formulation of solutions is most likely to slow the adoption and lessen confidence in the employees. These results may be attributed to the earlier research, which pointed to the significance of the strong IT architecture and the fit of the HRM systems to the overall business strategies (Parry and Strohmeier, 2014). Without technological preparedness, the practices of HR based on AI will be fragmented and half-baked (Leicht-Deobald et al., 2019).

Environmental barriers that are not very strong also define the adoption landscape. Factors such as unreliable vendor support, limited government backing, and disruptions like the COVID-19 pandemic contribute to uncertainty in implementation. It is also in line with the work by emerging economies because such factors as external institutional readiness and vendor credibility have been found to influence the extent of digital HR transitions and their enforcement (Ruel and Bondarouk, 2014; Meijerink et al., 2021). Internal capacity may exist in an organization, but the broader ecosystem of policy, relationships with vendors and national preparedness remains necessary to facilitate adoption.

Remarkably, people related barriers, such as lack of communication, poor training and leadership support though important, appear to be manageable as opposed to the organizational and technological ones. This can mean that any resistance or capability gaps at the workforce level can be bridged and most cases can be achieved with the assistance of certain interventions, which might involve training courses, leadership exercises, and changed communication strategies. People-related issues were mentioned as an important barrier in the previous studies (Strohmeier and Piazza, 2015), although the present-day data indicate that the given concerns may become secondary once the organization is proven to be structured well and technologically ready.

Taken together, these findings suggest that an AI adoption in HRM has a pyramid of barriers. Organizational factors are the most important ones followed by technological and environmental challenges and people-related barriers are more adaptable to managerial intervention. This does not only provide theoretical, but also practical knowledge: it simplifies the structures of technology adoption by turning the issue of organizational readiness to the core of the issue, and it also provides HR leaders with some practical information on where they need to deploy the resources. Enabling platforms and decision making processes, investing in scalable technology platforms, forming alliances with trustworthy vendors and simultaneously training and managing change among the employees are the best ways of integrating AI into HRM.

CONCLUSION

The proposed study was an attempt to examine the challenges that influence deployment of Artificial Intelligence in the Human Resource Management of IT organizations. The findings demonstrate that barriers to the adoption of AI are many-sided and concurrent in nature regarding the personnel, organizations, technology, and environment. Organizational barriers was the most significant of these and demonstrated the key role of resources, leadership, and culture as the elements of effective implementation. Technological issues, particularly those of IT infrastructure and compatibility of systems, and other extraneous factors, such as vendor support and policy preparedness, had an indirect impact as well. People-related concerns, although they did exist, appeared to be rather less intense and could be resolved successfully through a set of particular HR measures.

The results of the structural model validate the assumption that adoption is not a technical or significantly operational decision, but one that requires coordinance between the organizational preparedness, the technological capacity and the external ecosystem. Though it is agreeable that AI has the potential to streamline the administrative process, drive innovation and workforce development, there is lingering concern that AI can be used in sensitive HR practices such as recruitment and promotions. That means that the eradication of the shortcomings in structural and technological readiness can be attained via the establishment of trust, equity, and openness in the AI-based HR operations by organizations. In this manner, they can contain the problems of privacy, ethics, acceptance of the employees, which remain significant to the level of the sustainability of the organization in the long term.

In the practical sense, the study points out that IT firms should concentrate on leadership commitment, to invest in quality IT infrastructure, and to collaborate with reputable technology providers, and at the same time institute training and sensitization to enhance workforce readiness. Positive regulatory policies, and programmes driven by the government at the policy level, can also help strengthen organizational confidence in the application of AI-driven HR solutions. In total, the study contributes to the current knowledge base in digital HRM by empirically demonstrating the levels of barriers hierarchy and offering viable methods of traversing the boundary. Future researchers can use the current study to examine longitudinal adoption behavior or examine the outcome of the study in other sectors other than IT with the intention of arriving at a more generalized portrayal of the transformative nature of AI in HRM.

SCOPE FOR FURTHER RESEARCH

Despite the pertinent information about the obstacles affecting the implementation of Artificial Intelligence in Human Resource Management, the current study also creates opportunities to conduct new research. First, the research has been restricted to HR professionals in IT organizations which are more technologically advanced than the others. Future studies may apply the framework to other areas like manufacturing, medical, banking, and education in which AI use in HRM remains in its infancy to reflect cross-industry differences in challenges and levels of readiness.

Second, the study adopted a cross-sectional survey design, which would give a picture of employee perceptions at a single point of time. Longitudinal research might be implemented to focus on how the organizational, technological, and environmental challenges change over time and how the organizations overcome barriers one by one to adopt AI in HR practices. These designs would also allow the investigation of the paths of adoption and the long-term implications of AI-enabled HRM.

Lastly, the present research concentrated mainly on four types of barriers, namely, people, organizational, technological, and environmental. Researchers can add to the list of variables in the future including ethical factors, bias in the algorithm, data management, and employee confidence in AI systems. The quantitative results might be supplemented with the qualitative findings as well (interviews and case studies) due to the possibility to collect more detailed information about the lived experience of the HR professionals in the context of implementing AI. This increase in scope and methodology enables future studies to further develop theoretical models and has a role to play in the creation of best practices in AI-enabled HRM in a variety of organizational settings.

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