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Can AI Redefine Best Practices in Human Resources?

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Abstract: *We break the research into three phases. We first validated the HRBPS using an exploratory factor analysis (EFA), considering its structure and how faithfully it gauges what it is meant to be measuring. Using Cronbach's alpha to guarantee the consistency and reliability of the data, we then examined the validity of a second scale, that which gauges the degree of artificial intelligence impacting administrative decisions. Finally, we investigate how AI adoption in HR relates to the main characteristics of HRBPS and how general AI influences managerial decision-making through network analysis. In particular in areas such as recruitment, training and corporate culture molding, the results reveal that artificial intelligence is becoming more and more significant in HR procedures. Artificial intelligence has enabled businesses to make judgments grounded on data instead of gut feeling and operate more effectively. Still, there are questions regarding algorithm bias, lack of openness and possible human oversight loss. The network analysis also highlights the increasing complexity of AI's involvement in workforce management by showing how closely linked AI-driven decision-making is now with important HR operations. By verifying the HRBPS, evaluating how consistently we can quantify AI's influence in managerial choices and charting the relationships between AI and optimal HR practices, this study adds to the continuing conversation about artificial intelligence in HR. Future studies should expand on these results using long-term studies and confirmatory factor analysis (CFA) to better understand how managers decide and how artificial intelligence shapes HR strategies.*

Keywords: Artificial Intelligence, Human Resources, Best Practices, Organizational Processes, Decision Making.

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Introduction

Artificial intelligence (AI) is rapidly changing sectors, transforming corporate strategies and rethinking human resource (HR) policies. AI-driven solutions are progressively included in HR operations including talent management, organizational decision making, employee training and recruiting (Jiang et al., 2012). Although the adoption of artificial intelligence offers better efficiency, data-driven insights and better decision-making, worries about algorithmic bias, openness and the declining relevance of human intuition persist (Tambe et al., 2019). These advances begged a basic question: Can artificial intelligence redefine best practices in human resource management?

The present work investigates the interaction between HR best practices and AI-driven managerial decision making. Two main constructions are investigated: the Level of Implementation of Managerial Decisions through AI Scale (AIDM) and the Human Resource Best Practices Scale (HRBPS). The HRBPS uses four main basic dimensions: recruitment and selection, professional development and training, team relations and communication and organizational culture and values to evaluate views of HR practices. Meanwhile, the AIDM scale gauges how much artificial intelligence shapes management decision-making processes.

Although previous studies have looked at how artificial intelligence (AI) could be used in HR management, few have methodically looked at how AI-driven decision-making interacts with accepted HR best practices (Stone et al., 2015). Most research on particular factors of AI adoption, such as automated recruiting systems or AI-assisted performance evaluation, ignores its wider effects on organizational culture and human-centered leadership (Paulet et al., 2021). Using an exploratory factor analysis (EFA) of HRBPS, validating the AI-driven managerial decision-making scale, and applying a network analysis to trace the interactions between AI and HR practices, this work seeks to close this gap.

This work aims to investigate the factorial structure and validity of the HRBPS by means of exploratory factor analysis (EFA) and to measure the reliability of the AI-driven managerial decision-making scale (AIDM) by Cronbach's alpha. Furthermore, a network analysis is done to investigate the relationship between the adoption of artificial intelligence with important HR aspects. The study forms the following hypothesis depending on previous studies and theoretical considerations.

H1: Recruitment and selection best practices are favorably connected with managerial decision implementation led by artificial intelligence.

Professional growth and training possibilities are favorablely connected with H2: AI-driven managerial decision implementation.

H3: Team relations and communication dynamics are closely linked with AI-driven managerial decision-making application.

H4: Organizational culture and values clearly correspond to AI-driven managerial decision implementation, therefore influencing leadership styles and workplace norms.

By tackling these hypotheses, this study offers empirical understanding of the changing function of artificial intelligence in HRM, therefore supporting both scholarly publications and useful HR policies.

Literature review

The integration of artificial intelligence (AI) into human resource management (HRM) has fundamentally changed conventional HR methods and presents both possibilities and difficulties

(Murire, 2024). The effects of artificial intelligence on important HR operations—including recruiting and selection, professional development and training, team interactions and communication, corporate culture and values—are investigated in this overview of the research.

By automating tasks that include candidate matching and resume screening, artificial intelligence has transformed hiring. Studies have indicated that the use of artificial intelligence improves the applicant experience, resulting in better qualified candidates (Florea & Croitoru, 2025). Still, there are difficulties like possible biases of the artificial intelligence algorithm and questions regarding the validity of applicant assessments when AI instruments are applied during interviews.

AI fills in skill shortages and offers tailored learning opportunities, therefore improving professional growth. Companies are using artificial intelligence to assess staff competencies, make plans for growing demand and provide customized training courses. But including artificial intelligence in training calls for moral values to guarantee fairness and efficacy (Gélinas et al., 2022).

Team communication is improved and employee sentiment is tracked using artificial intelligence tools more and more. Through the pattern analysis of communication and feedback, artificial intelligence can spot possible team problems and offer solutions to enhance dynamics. But sometimes the impersonal character of artificial intelligence contacts causes employees to feel alienated.

Adoption of artificial intelligence in HRM improves data-driven decision making and efficiency, therefore influencing company culture. By automating repetitive administrative tasks, artificial intelligence lets HR experts concentrate on key projects and staff participation. Integrating artificial intelligence, however, also raises ethical questions like guarantees of openness, preservation of justice and preservation of the human element in HR procedures (Nosratabadi et al., 2022).

Although artificial intelligence has many advantages, it also brings problems, including data privacy issues, possible biases in decision-making algorithms and the necessity of ongoing observation to guarantee moral use. Companies must strike a balance between the need for human supervision to uphold fairness and confidence in HR operations and the increases in efficiency from artificial intelligence (Gikopoulos, 2019).

By including artificial intelligence into HRM, conventional methods are being changed and data-driven insights are provided by increased efficiency. To fully utilize AI's ability to revolutionize HR operations, companies must, however, negotiate the related difficulties and ethical questions.

Methodology

Participants

The survey included 289 workers from different companies ranging in age from 18 to over 50 years. The sample consisted of 108 men (37.4%) and 181 women (62.6%). Educational backgrounds ranged: 15.6% finished high school or post-secondary education, 50.2% had a bachelor's degree, 28.4% had a master's degree and 5.9% had a doctorate degree. Among the many sectors represented, the participants were from energy, banking, manufacturing and services. Roles ranged from high management (12.8%) to middle management (28.7%), to nonmanagerial roles (58.5%). Tenure within companies ranged from 20.4% with less than one year, 47.1% between one and five years, 22.8% between six and ten years, and 9.7% over ten years. About artificial intelligence experience, 15.2% said none, 53.3% said minimal, 25.6% said moderate and 5.9% said advanced.

Instruments

Inspired by current research on best practices in human resource management (HRM) and artificial intelligence-driven managerial decision making, the study used two main instruments created by our team. These tools were meant to record staff opinions on HR policies and the degree of application of artificial intelligence in managerial decision-making procedures.

Constructed using theoretical frameworks and empirical research on HR policy and organizational behavior, the Human Resource Best Practices Scale (HRBPS) is the scale that evaluates four aspects: recruitment and selection; professional development and training; team relations and communication; organizational culture and values. There are 20 items total, each scored on a 5-point Likert scale between 1 (strongly disagree) and 5 (strongly agree). With a Cronbach alpha of 0.97, thereby showing great reliability, exploratory factor analysis (EFA) and reliability testing verified its factorial structure and internal consistency.

Designed to assess how much artificial intelligence is included in different managerial decision-making procedures, the AI-Driven Managerial Decision Implementation Scale (AIDM) Previous studies on AI adoption in HRM (Kim et al., 2021; Palos-Sánchez et al., 2022) informed this scale, which comprises ten items that measure AI use in strategic decision-making, recruitment, performance evaluation, talent identification, performance monitoring and HR policy implementation. Using a 5-point Likert scale, the responses ranged from 1 (Never) to 5 (Always). With a Cronbach alpha of 0.97, the scale showed great internal consistency, therefore verifying its reliability for evaluating AI-driven decision-making strategies.

A pilot study helped both instruments to be pre-tested and polished, thus guaranteeing psychometric validity, clarity and relevance. The participants were given the last versions as part of a larger survey, which offered information on HR best practices and the integration of artificial intelligence into managerial decision-making.

Procedure

Online professional networks, trade groups and organizational alliances were used to find participants, ensuring a varied and representative sample in several professional sectors. Before participating, participants received comprehensive study materials that included information on ethical issues, research goals and their right to quit at any time without penalty. Before starting the survey, informed consent was gathered.

Using a secure online platform, the survey was answered anonymously, therefore, reducing response bias and guaranteeing participant anonymity. There were three primary factors in the questionnaire: demographic data; the Human Resource Best Practices Scale (HRBPS); and the AI-Driven Managerial Decision Implementation Scale (AIDM). Participants may finish the survey whenever it would be most convenient within a four-week data collection period. Strict data security procedures were implemented to preserve confidentiality and data integrity, therefore, upholding ethical research norms by excluding personally identifiable information.

Analysis Plan

Multistage data analysis guaranteed a strong review of the study variables and their interrelations. Initially, HRBPS underwent exploratory factor analysis (EFA) to evaluate its factorial structure, pinpoint latent constructions and so establish its relevance in the study setting. Potential correlations among components were enabled by factoring in the principal axis with oblique rotation.

Second, internal consistency of the HRBPS and the AIDM scales was evaluated by means of Cronbach's alpha, guaranteeing that every construct showed a high degree of measurement stability.

Third, descriptive statistics, mean, standard deviation, minimum and maximum values, were calculated to aggregate participant responses across important variables, therefore providing information on central patterns and data set variability.

Fourth, perceptions of HR best practices and the use of artificial intelligence in managerial decision-making were investigated using Pearson's correlation analysis. These studies examined the direction and intensity of relationships between conventional HR operations and artificial intelligence-driven technologies.

Finally, the interconnections between artificial intelligence and the four HRBPS aspects were visualized and interpreted using network analysis. This method allowed important nodes and routes to be found, showing how AI-driven decision making interacts with recruitment, training, team relations and organizational culture (Tang et al., 2018). Emphasizing both direct and indirect effects on workplace dynamics, the results of the network analysis provide a complete picture of how artificial intelligence shapes HRM tactics.

Results and discussions

Exploratory Factor Analysis (EFA)

Principal axis factoring (PAF) with promax rotation was used to evaluate the factorial structure of the Human Resource Best Practices Scale (HRBPS) and the AI-Driven Managerial Decision Implementation Scale (AIDM).

To support the factorability of the correlation matrices, the Kaiser-Meyer-Olkin (KMO) test found outstanding sampling adequacy for HRBPS (KMO = 0.959) and AIDM (KMO = 0.959). Bartlett's test of sphericity was also noteworthy for both scales ($p <.001$), which verified the fit of the data for factor analysis.

The four-factor solution disclosed by the EFA findings for HRBPS matched the theoretical framework of recruitment and selection, professional development and training, team relations and communication, and corporate culture and values. Strong item-factor interactions were shown by factor loadings ranging from 0.615 to 0.686. The four components' combined variance explained—78.2%—suggesting a clearly defined structure.

With the 10 items loading strongly on one underlying construct (factor loadings between 0.758 and 0.946), EFA obtained a single-factor solution for the AIDM scale, therefore, accounting for 78.9% of the variation. This validates that the scale adequately captures the unidimensional concept of AI-driven decision implementation in managerial processes.

To support the robustness of the acquired components, further fit indices revealed a good fit of the model (RMSEA = 0.063, TLI = 0.964, CFI = 0.981 for HRBPS; RMSEA = 0.203, TLI = 0.865, CFI = 0.895 for AIDM).

Principal axis factoring (PAF) with promax rotation was used in an exploratory factor analysis (EFA) to evaluate the factorial structure of the Human Resource Best Practices Scale (HRBPS) and verify the underlying dimensions. This method was used to consider the anticipated relationships among the dimensions of HR best practice.

With a 0.959 Kaiser-Meyer-Olkin (KMO) score of sample adequacy, factor analysis would fit quite well. Bartlett's test of sphericity was also significant ($\varphi^2(190) = 6391.711$, $p = 0.001$), therefore confirming the fit of the data for factor extraction.

An initial eigenvalue analysis indicated a five-factor solution; yet the fifth component had poor loadings and conceptual overlap with other factors. Consequently, a four-factor solution was kept and confirmed that the factors obtained sufficiently reflect the data, since it explained 78.2% of the total variance. Taking into account important organizational factors, the last solution is in accordance with the conceptual framework of HR best practices.

Table 1. Factor Loadings

Item	Factor 1	Factor 2	Factor 3	Factor 4	Uniqueness
HR23	0.919				0.183
HR25	0.876				0.168
HR22	0.871				0.146
HR21	0.849				0.170
HR24	0.767				0.185
HR13		0.942			0.202
HR15		0.850			0.167
HR12		0.816			0.193
HR14		0.803			0.131
HR11		0.654			0.198
HR3			1.000		0.158
HR4			0.867		0.210
HR5			0.854		0.180
HR2			0.837		0.214
HR1			0.455		0.465
HR7				0.986	0.155
HR8				0.746	0.287
HR10				0.648	0.252
HR6				0.638	0.212
HR9				0.615	0.275

Note: Promax rotation was applied.

Source: Authors' own research.

With loadings between 0.767 and 0.919, factor 1—organizational culture and values—includes items HR23, HR25, HR22, HR21 and HR24. Reflecting the degree to which staff members feel their company creates a welcoming workplace, these objects capture ideas of organizational culture, value alignment and ethical HR procedures. The high loadings imply that HR best practices are significantly shaped by business culture, hence stressing the significance of matching employee expectations with corporate values.

With loadings between 0.654 and 0.942, factor 2—team interactions and communication—includes items HR13, HR15, HR12, HR14 and HR11. These tools reflect workers' impressions on internal communication, teamwork and cooperation within the company. High factor loadings show that HR policies are mainly dependent on team relations, which influences employee involvement, conflict resolution and general workplace harmony.

Factor 3: Professional growth and training consist of items HR3, HR4, HR5, HR2 and HR1 with factor loadings between 0.455 and 1.00. These products show how companies help staff develop their skills, advance their careers and find learning opportunities. The high loadings on this element imply that views of HR effectiveness are much shaped by access to training programs and activities for career advancement. HR1's quite modest loading (0.455) points to some variance in how training opportunities are seen throughout various companies.

With loadings between 0.615 and 0.686, factor 4: recruitment and selection comprise factors HR7, HR8, HR10, HR6 and HR9. These products capture staff impressions of recruiting policies, fairness in recruitment and openness about selection. The high load of HR7 (0.686) indicates that workers significantly link artificial intelligence-driven hiring with their entire HR experience, therefore, underscoring the increasing importance of technology in talent acquisition.

With RMSEA = 0.063, TLI = 0.964 and CFI = 0.981—all of which indicate an outstanding model fit - the four-factor model that was obtained showed a great statistical fit. Each factor's Cronbach's alpha value exceeded 0.90, therefore, attesting to great internal consistency and reliability. The findings demonstrate that HRBPS reasonably reflects important characteristics of HR best practice, which supports the conceptual importance of organizational culture, communication, training and recruitment as the main foundations of HR effectiveness.

Descriptive statistics were calculated for the four dimensions of the Human Resource Best Practices Scale (HRBPS) to provide an understanding of the general distribution of responses and participants' opinions of HR best practices. Mean scores and standard deviations give a general picture of employee ratings at every HR area in different companies.

Table 2. Descriptive statistics for HRBPS subscales

	N	Minimum	Maximum	Mean	Std. Deviation
recruitment and selection	289	1.00	5.00	3.4747	1.13625
professional development and training	289	1.00	5.00	3.3765	1.14795
team relations and communication	289	1.00	5.00	3.5599	1.13066
organizational culture and values	289	1.00	5.00	3.4450	1.19201
Valid N (listwise)	289				

Source: Authors' own research.

With a mean score of 3.56, SD = 1.13, team relations and communication got the highest mean score, suggesting that workers were quite happy with workplace cooperation, communication and interpersonal dynamics. The smaller standard deviation points to a more consistent participant perception.

Although the difference in responses indicates some diversity in experiences between companies, the positive rating for recruitment and selection (M = 3.47, SD = 1.14) suggests that recruiting procedures are generally thought to be fair and successful.

Showing a somewhat lower mean, Organizational Culture and Values (M = 3.44, SD = 1.19) indicated modest satisfaction with business culture and value congruence. The higher standard deviation (SD = 1.19) points to increased response variability, which means that some workers may find great cultural compatibility while others may not.

With a mean of M = 3.38, SD = 1.15, Professional Development and Training (M = 3.38, SD = 1.15) had the lowest mean, therefore, indicating that staff members might view a lack of appropriate opportunities for professional advancement, organized training courses, or skill development projects.

Across the four HR measures, the recorded standard deviations - which range from 1.13 to 1.19—indicate somewhat modest variation in the impressions of the participants. This implies that depending on their corporate setting, some employees may encounter discrepancies even if others follow well-defined HR procedures.

Pearson's correlation analysis was used to investigate the links between HR best practices and the implementation of AI-driven managerial decisions. The intensity and direction of the links between the integration of artificial intelligence in decision-making and the four HR dimensions, recruitment and selection, professional development and training, team interactions and communication and organizational culture and values, are evaluated in this paper.

Table 3. Correlation analysis

Variable	AI-Driven Decision Implementation	Recruitment & Selection	Professional Development & Training	Team Relations & Communication	Organizational Culture & Values
1. AI-Driven Managerial Decision Implementation	—	0.212***	0.245***	0.218***	0.222***
2. Recruitment & Selection	0.212***	—	0.764***	0.700***	0.602***
3. Professional Development & Training	0.245***	0.764***	—	0.785***	0.752***
4. Team Relations & Communication	0.218***	0.700***	0.785***	—	0.782***
5. Organizational Culture & Values	0.222***	0.602***	0.752***	0.782***	—

*Note: *** p < .001*

Source: Authors' own research.

Confirming that greater integration of AI in decision-making processes is linked with enhanced HR practices, the results show statistically significant positive correlations between the implementation of AI-driven managerial decisions and all four HR dimensions.

The implementation of AI-driven decision and professional development & training showed the strongest link ($r = 0.245$, $p < .001$), implying that companies that use AI into their management operations typically offer more ordered and flexible employee training programs. This outcome complements H2, therefore, underlining the idea that, by means of automated learning platforms, customized development plans and data-driven skill assessments, artificial intelligence improves worker upskill and career progression activities. Real-time identification of skill gaps and training requirements by artificial intelligence helps companies to provide focused professional development initiatives, therefore optimizing learning and customizing it to meet employee demands.

AI-driven decision making and company culture & values revealed a similarly substantial correlation ($r = 0.222$, $p < .001$). This result validates H4, which means that value alignment, ethical HR policies and corporate strategy are under increasing influence of artificial intelligence. Including artificial intelligence in HR policy implementation, employee monitoring and engagement analytics ensures that HR strategies complement business values. By means of AI-driven data, HR managers can identify patterns in employee well-being, workplace inclusiveness and engagement levels, which allows companies to build a more harmonic and flexible culture.

Putting emphasis on the role of AI in improving workplace cooperation and accelerating team interactions, the association between AI-driven decision making and team relations and communication (r = 0.218, p =.001) supports H3. Using improved communication patterns, early conflict detection and workflow efficiency optimization – all of which AI-powered analytics can accomplish – better coordination and employee cooperation result. Applications of artificial intelligence, such as predictive sentiment analysis, virtual assistants and chatbots, are being utilized more and more to support cross-functional cooperation, streamline workplace interactions and guarantee effective processing and action upon employee comments.

Ultimately, recruitment and selection (r = 0.213, p <.001) was strongly related to AI-driven decision-making, therefore confirming H1. Although artificial intelligence is increasingly used in competency-based tests, automated resume sorting and candidate screening, this association indicates that human decision making still moderates its impact in recruitment. Companies still depend on human supervision for final employment decisions to ensure that AI-driven procedures enhance rather than replace conventional selection criteria. Recent research has well documented the use of artificial intelligence in lowering hiring bias, enhancing candidate matching and simplifying the recruiting process; yet, these results imply that companies are still in a transition stage, juggling automation with human judgment in hiring processes.

A network analysis was performed to investigate the connections between HR best practices and artificial intelligence-driven decision making. This method shows the structure of interactions between variables, therefore exposing the link between important HR operations and AI integration into managerial decisions. Stronger connections are intuitively shown in the network graph in Figure 1 by thicker edges, whereas weaker connections show as thinner lines.

Five nodes make up the network, which correspond to the four HR best practice dimensions (Nodes 2–5) and AI-driven decision implementation (Node 1). Nine nonzero edges out of ten possible connections expose a sparsity of 0.10, suggesting that most HR aspects are related via AI-driven decision-making, but some ties remain weak or indirect.

The measures calculated to evaluate the relative impact of every variable in the network were network centrality measures. Betweenness, proximity, strength and predicted influence are the four centrality measurements that help to discover the most important factors influencing HR practices.

With a particularly great betweenness (1.789), closeness (1.008) and strength (1.013), Professional Development and Training (Node 3) displayed the best centrality scores in most criteria. This suggests that acting as a vital middleman in the network, training and development help to link artificial intelligence-driven decision-making with other HR policies. The close relationships among professional growth, team communication and corporate culture imply that the integration of artificial intelligence into workforce education has a large impact on HR operations.

With a low strength value (-0.153) and minimal direct influence on other HR aspects, recruitment and selection (Node 2) shown somewhat poor influence on the network. This implies that, perhaps because of ongoing reliance on human supervision in hiring decisions, AI's influence on training or team dynamics is more important than its part in recruiting. Potentially, recruiting is only marginally correlated with team relations, suggesting that artificial intelligence-driven hiring could potentially affect organizational integration and employee satisfaction.

With closeness (0.309) and strength (0.615), Team Relations and Communication (Node 4) showed modest connectedness, underlining how clearly AI-driven decision-making affects workplace relationships. This supports the correlation results by implying that human factors remain significantly influential in workplace relationships even if artificial intelligence can improve team coordination and HR procedures.

With closeness (0.198) and strength (0.125), Organizational Culture and Values (Node 5) displayed little interconnectedness, suggesting that artificial intelligence impacts business culture, albeit in a more indirect way. Although primarily through its effects on staff growth and team interactions, the links between organizational culture, training and communication imply that AI-enhanced decision making helps to shape cultural norms and values.

With negative values for betweenness (-0.447), proximity (-1.680) and strength (-1.599), AI-Driven Managerial Decision Implementation (Node 1) had the lowest centrality scores across all measurements. This implies that, with its effects mediated through other HR processes, AI itself is an enabler rather than a direct driver of HR best practices. Stated differently, AI-driven decision-making affects HRM through interactions with training, team communication and attempts at culture building rather than acting in a vacuum.

Table 4. Centrality measures per variable

	Network			
Variable	**Betweenness**	**Closeness**	**Strength**	**Expected influence**
Level of implementation of managerial decisions through AI	-0.447	-1.680	-1.599	-1.599
Recruitment and selection	-0.447	0.164	-0.153	-0.153
Professional development and training	1.789	1.008	1.013	1.013
Team relations and communication	-0.447	0.309	0.615	0.615
Organizational culture and values	-0.447	0.198	0.125	0.125

Source: Authors' own research.

These conclusions are shown graphically in Figure 1 by the network graph. Stronger correlations are shown by thicker lines. The clearest connections are found between corporate culture (Node 5), team communication (Node 4) and professional growth (Node 3). The weaker link between AI-driven decision making (Node 1) and recruitment (Node 2) indicates AI's more restricted influence in hiring than in other HR operations.

The way the network is structured emphasizes how professional development mostly mediates AI integration in HR, therefore, underlining the need of training as a link between AI acceptance and HR best practices. This is consistent with new research that stresses the role predictive analytics, adaptive training courses and AI-powered learning platforms play in the formation of current workforce development plans (Tambe et al., 2019; Stone et al., 2015).

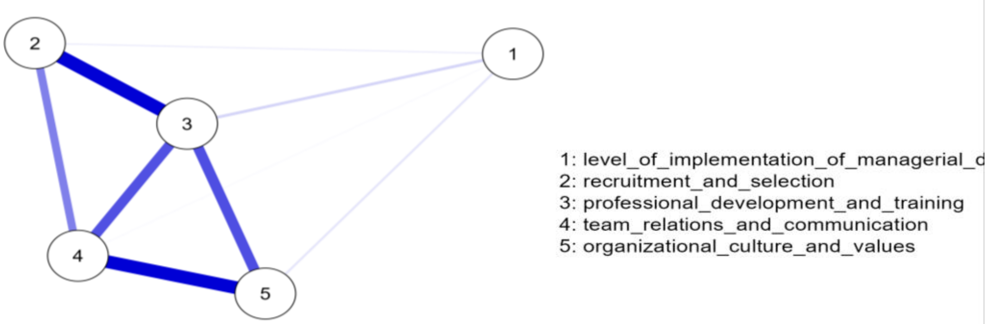

Figure 1. Network

Source: Authors' own research.

Discussions and limitations

The results of this study confirm the important, yet indirect, influence of artificial intelligence-driven decision making in HRM by empirical support for its integration. Emphasizing the need for recruitment and selection, professional development and training, team interactions and communication and corporate culture and values, the results of the Exploratory Factor Analysis (EFA) confirmed the four-factor structure of the HR Best Practices Scale (HRBPS). The solid psychometric qualities of the scale are reinforced by the strong factor loadings and model fit indices; hence the scale is a useful instrument for evaluating the influence of artificial intelligence on HR operations.

All four HR best practice categories are favorably correlated with artificial intelligence-driven decision-making, according to the correlational study. Integration of AI and professional development & training showed the strongest association, implying that companies make good use of artificial intelligence to improve employee learning, personalize training and support career growth. This result is consistent with earlier studies showing that AI-powered learning management systems improve workforce up-skilling and adaptive training experiences (Tariq, 2024; Khamis, 2024).

Network analysis revealed that professional development and training act as a crucial node linking artificial intelligence-driven decision making with other HR dimensions, therefore offering further insight into the structural interactions between AI and HR activities. The rather less direct impact of artificial intelligence on recruiting and selection implies that even if AI improves hiring efficiency, companies still mostly rely on human judgement for the final choice. The results show that integration of artificial intelligence into training programs has the largest effect on its acceptance in HRM, therefore supporting its function as a facilitator rather than a stand-in decision maker in HR procedures.

Notwithstanding these encouraging revelations, the study also draws attention to some difficulties with incorporation of artificial intelligence into HRM. In particular in recruitment and performance reviews, one major issue is the possible bias in HR decision making caused by artificial intelligence. AI systems taught in past HR data could unintentionally reinforce prejudices, hence producing distorted talent assessments or discriminatory hiring practices (Kumari et al., 2024). To reduce these hazards, companies have to ensure that AI systems are always updated, audited and ethically monitored.

Balancing automation with human supervision is still another difficulty. The findings imply that artificial intelligence improves efficiency, but cannot replace in HRM human intuition and interpersonal judgement. This is consistent with earlier studies showing that rather than replacing human decision-making, artificial intelligence should be seen as an augmentative tool (Leyer & Schneider, 2021; Trifan et. Al., 2023). To maintain a human-centered AI approach in HRM, companies must establish explicit ethical guidelines and governance rules.

Although this study offers important insights on the use of artificial intelligence in HRM, it has some shortcomings that should be resolved in next studies. First, the study relied on self-reported data, which can be biased by social desirability. Participants may have responded in line with organizational expectations rather than their own experiences or inflated their knowledge of AI tools. Future research should combine objective HR performance measurements or artificial intelligence use analytics to augment self-reported data.

Second, the cross-sectional character of this study avoids causal conclusions. Although HR best practices and AI-driven decision making showed strong correlations, it is yet unknown whether AI adoption directly results in improvements in HR operations or if well-run HR systems are more likely to apply AI. A deeper understanding of causal links and long-term implications on HRM would come from longitudinal research that tracks artificial intelligence usage over time.

Third, the study sample comprised particular sectors and geographical areas, therefore perhaps restricting the generalizability of results. With some sectors (e.g., tech and finance) driven more by artificial intelligence and others (e.g., education and healthcare) depending more on human-centered HR strategies, AI adoption in HRM may vary greatly between sectors. Future studies should look at industry-specific AI adoption trends and look at how HR's AI implementation is impacted by organizational size and structure.

Finally, the research concentrated mostly on how artificial intelligence affected HR procedures rather than employee opinions on AI adoption. Although AI-driven decision making can maximize HR effectiveness, its application depends on employee acceptance and confidence in AI technologies. Future studies on employee attitudes towards artificial intelligence in HRM should look at factors such as AI openness, trust and seeming fairness in AI-driven judgments.

Conclusions

This article shows empirical data that confirm the role that artificial intelligence-driven decision-making plays in HRM and its favorable effect on HR best practices. Although correlation and network analyses underlined AI's central relevance in training, recruitment and team communication, the factorial validation of the HR Best Practices Scale (HRBPS) proved its reliability and structural integrity. The results imply that artificial intelligence supports strategic HR activities by optimizing decision making and so acts as a facilitator of HR procedures.

The findings highlight how much professional development and training define AI's most important influence; secondary effects on corporate culture and team interactions follow from these results imply that companies should give AI-driven learning projects, adaptive training programs and AI-supported talent management top priority so as to exploit AI's advantages in HRM. The study does, however, also underline important issues including bias concerns, the requirement of ethical supervision and the need to strike a balance between automation and human knowledge.

Practically, companies trying to apply artificial intelligence in HR should focus on three main ideas. First, creating AI-powered career development and training programs will help improve workforce skills and future-proof workers against changing job needs. Second, reducing bias and maintaining ethical HR norms depend on guarantees of AI transparency and fairness in hiring and decision-making procedures. Maintaining human supervision and ethical governance systems will ultimately help to balance artificial intelligence automation with human-centric decision-making, so ensuring that AI enhances rather than replaces human HRM knowledge.

Future studies should investigate longitudinal effects, industry-specific AI adoption patterns and employee opinions on artificial intelligence in HR as AI acceptance in HR continues to change. Organizations can use artificial intelligence as a strategic HR tool by tackling these issues, thus guaranteeing fairness, inclusion and ethical alignment in workforce management.

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