Analysis of the Use and Impact of Artificial Intelligence on Managerial Decisions and Organizational Processes

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Abstract: *Artificial intelligence (AI) is altering the hiring, training and management of staff in companies, thus transforming decision-making in human resource management (HRM) from past data-driven to present. This paper examines how artificial intelligence is changing HR best practices and highlights the main factors influencing AI adoption and the consequent effects on organizational effectiveness. We investigate how employee's digital abilities, artificial intelligence experience and self-confidence in using technology impact AI integration in HRM through exploratory factor analysis (EFA), correlation analysis, network analysis, and decision tree regression. Although age and education have just a small impact, the results reveal that digital competency is the largest driver of AI adoption followed by artificial intelligence experience and self-efficacy. However, the adoption of artificial intelligence is not without difficulty. The main obstacles for companies trying to include artificial intelligence into HR are algorithmic bias, openness issues and ethical dangers. Organizations should invest in AI-focused training programs, guarantee fairness in AI-driven hiring and evaluations, and maintain human supervision to balance automation with ethical decision making to maximize AI while avoiding these risks. Future studies should investigate how the acceptance of artificial intelligence in HR changes over time, how it affects other sectors and how employees really feel about collaborating with HR systems driven by artificial intelligence. AI has great potential to improve HR efficiency and decision making with proper application; yet its success depends on ensuring it remains inclusive, ethical and transparent even as such.*

Keywords: Artificial intelligence, managerial decision-making, human resource management, AI adoption, organizational processes.

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Introduction

Rapidly changing how companies handle their workforce, artificial intelligence (AI) is improving HR procedures using data-driven, predictive and efficient means (Shrestha et al., 2019). AI is becoming a useful tool for HR experts (Rajagopal et al., 2022) from automating recruiting to improving staff planning and performance assessments. Although AI has interesting opportunities, its use presents ethical governance, transparency and algorithmic bias problems (El Khatib & Al Falisi, 2021). Ensuring that artificial intelligence improves rather than replaces human decision making in HR depends on finding the right mix between automation and human supervision.

Companies are increasingly using artificial intelligence to raise professional development, employee engagement and hiring accuracy. Analyzing massive data sets, AI-powered systems can forecast talent success, simplify onboarding procedures and maximize personnel management (Trunk et al., 2020). However, the adoption of artificial intelligence is not always seamless; many companies deal with employee opposition, low AI literacy and questions about justice in AI-driven choices (Rajagopal et al., 2022). The degree to which artificial intelligence is incorporated into HR operations depends mainly on employees' knowledge of organizational culture, managerial support and AI (Shrestha et al., 2019).

Although interest in artificial intelligence-human resource management is rising, knowledge about the factors influencing AI adoption still lags behind. Most of the research have concentrated on how artificial intelligence increases efficiency (El Khatib & Al Falasi, 2021) or its technological capacity (Rajagopal et al., 2022). Meanwhile, less attention has been paid to human factors—such as digital familiarity, artificial intelligence experience and personal decision-making style—that influence AI involvement in HR (Trunk et al., 2020). Furthermore, it is underdeveloped how AI-driven decision-making interacts with conventional HR best practices, including company culture, training and recruitment.

Lacking in current research are machine learning applications in AI-HRM studies. Although conventional statistical approaches such as structural equation modeling (SEM) and regression have been extensively applied, they could oversimplify the intricate connections that influence AI adoption. This work uses decision tree regression, a machine learning method that detects nonlinear patterns without assuming a predefined model structure by use of hierarchical interactions among variables (Shrestha et al., 2019).

Focusing on digital familiarity, artificial intelligence experience and self-efficacy as the main drivers of AI adoption, the article seeks to examine how artificial intelligence affects HR decision making. It also looks at the moral questions and possible prejudices related to HR-driven artificial intelligence-driven decision-making. Because it offers a clear, understandable breakdown of how various factors contribute to AI adoption, stressing thresholds of AI proficiency and digital literacy that led to notable changes in engagement, decision tree regression was selected as the main analytical technique (El Khatib & Al Falisi, 2021).

This paper presents a data-driven view on artificial intelligence adoption in HR using decision tree regression, therefore, offering useful insights for companies wishing to include AI in a way that is ethical, fair and efficient. These results guarantee openness, responsibility and human-centric decision-making, therefore enabling companies to maximize their AI-driven HR strategies.

Literature review

Integration of artificial intelligence (AI) into human resource management (HRM) has fundamentally changed established HR operations, improving efficiency, decision-making and workforce management (Giraud et al., 2023). Automated recruitment, predictive analytics for talent acquisition and AI-driven staff performance monitoring (Noponen, 2019) are just a few of the HRM uses for AI. While supporting strategic business goals, these technologies simplify HR processes. However, despite its advantages, employees' digital competency, managerial experience with AI and decision-making style determine AI's efficacy in HRM mostly (Kovačić et al., 2022).

Employee familiarization with digital environments is the degree of comfort employees have with and skill in digital technologies and artificial intelligence applications. The adoption of artificial intelligence in HRM is mainly determined by this familiarity since employees who are more technologically literate are more likely to interact properly with AI-based HR systems (Olan et al., 2022). Higher digital literacy has been linked, according to research, to greater acceptance of AI-based decision making, improving employee happiness and HRM effectiveness (Alasmri & Basahel, 2022). Organizations therefore must make investments in digital training initiatives to ensure that staff members acquire the required skills to operate with artificial intelligence-driven HR systems.

Another important factor that influences AI adoption in HRM is the degree of experience that managers and staff members have with artificial intelligence. AI-literate managers often make better, data-driven decisions by efficiently using AI insights (Jarrahi, 2018). Managers with significant AI experience are more likely to trust AI recommendations, enabling AI to improve strategic decision-making procedures (Kovačić et al., 2022). However, lack of artificial intelligence experience might cause mistrust, opposition and overreliance on conventional HR methods (El Khatib & Al Falisi, 2021). To optimize AI's organizational influence, initiatives for AI training must aim for both HR professionals and decision-makers.

Although artificial intelligence-driven HRM has many benefits, its use raises operational and ethical issues. Algorithmic bias—where artificial intelligence systems inadvertently support preexisting prejudices in HR decision-making—is a big issue (Rodgers et al., 2023). Furthermore, the lack of openness in artificial intelligence decision making raises questions about responsibility and confidence in AI-driven HRM (Abusweilem & Abualoush, 2019). Organizations must therefore create AI governance systems that emphasize openness, bias detection and ethical supervision in AI-powered HR processes (Olan et al., 2022).

The adoption of artificial intelligence is highly influenced by a person's self-efficacy, that is, their conviction in their ability to effectively complete tasks. Higher self-efficacy employees are more likely to see artificial intelligence as a tool for enhancement than as a threat (Jarrahi, 2018). Studies reveal that workers who are more confident in their technological abilities accept AI-driven HRM systems (Giraud et al., 2023). This emphasizes the requirement of organizational support systems including user-friendly AI interfaces and AI training courses to increase employee confidence in AI-driven HRM.

Two main cognitive styles affect HRM decision-making: logical and intuitive methods (Alasmri & Basahel, 2022). More likely to believe AI-generated recommendations are rational decision makers, who depend on methodical analysis and data-driven insights (El Khatib & Al Falisi, 2021). On the contrary, intuitive decision makers rely on experience and gut emotions, which could cause opposition or mistrust of AI-driven decisions (Rodgers et al., 2023). Designing AI systems that allow different decision-making preferences and promote more AI adoption in HRM depends on awareness of various approaches.

This paper uses the Technology-Organization-Environment (TOE) framework to investigate the adoption of artificial intelligence in HRM since it clarifies how companies embrace new technologies depending on technological, organizational and environmental aspects (Jarrahi, 2018). While the environmental component takes into account industrial standards and ethical issues, the technological component comprises AI capabilities and digital literacy; the organizational component consists of employee self-efficacy and decision-making styles (Noponen, 2019). Guiding companies in properly using AI while addressing its ethical and operational problems, the TOE framework offers a disciplined method to grasp the drivers and obstacles of AI adoption in HRM (Abusweilem & Abualoush, 2019).

Methodology

Participants

Recalled via online questionnaires and organizational collaborations, the study sample consisted of 289 workers from various sectors and backgrounds. Participants were asked to provide demographic data such as age, gender, education level, industry, job role, tenure inside the company and knowledge of artificial intelligence technologies.

In terms of age distribution, the participants ranged from under 25 to over 55 years old. Most fell between the 25–44 age range (48.1%), therefore, indicating a rather young and mid-career workforce. Reflecting possible gender disparities in HR-related roles, the gender breakdown revealed that 67.2% of respondents were female and 31.8% were male.

Regarding their educational background, most participants had higher degrees: 47.4% have a bachelor's degree, 38.1% have a master's degree and 3.8% have a doctorate degree. With just 10.7% of the respondents having a high school or vocational education, most of the participants had a significant intellectual background, which is especially pertinent when considering how artificial intelligence can affect HRM.

With other sectors providing lower proportions, participants came from finance (13.8%), industrial production (2.8%), healthcare (8.7%), education (17.6%) and technology (12.5%). Employees in nonmanagerial roles accounted for the biggest occupational group (52.2%), followed by middle management (25.6%) and top management positions (11.8%), thus reflecting a wide spectrum of professional functions in corporate decision-making.

Work tenure ranged from 45.3% of workers having between 6–10 years of experience to 36.3% with 1–5 years and 18.3% with less than one year in their present company. This distribution points to a sample made up of well-seasoned experts with established careers.

Finally, the participants expressed different degrees of experience with artificial intelligence: 47.4% had minimum exposure, 36.0% had intermediate expertise and only 3.8% identified themselves as AI specialists. This spectrum of AI knowledge revealed how various degrees of artificial intelligence knowledge affect HR policies and decision-making procedures.

Instruments

Using six validated measures, each intended to evaluate various aspects of AI integration, HR best practices and decision-making styles, the study sought to evaluate the contribution of AI-driven decision-making in HRM. To guarantee validity and reliability, the scales were created using accepted psychological assessments in line with previous research.

This nine-item scale gauged workers' degree of knowledge about digital HR systems and artificial intelligence tools used in their company. The scope addressed topics including digital literacy, artificial intelligence-assisted hiring and automation in HR systems. The development of items was guided by previous studies on digital transformation in HR (Bondarouk & Brewster, 2016; Marler & Fisher, 2013). With Cronbach's $\alpha = 0.924$, the scale showed great internal consistency, thus verifying its reliability in evaluating employees' digital adaptability.

This ten-item scale gauged how closely managerial procedures included artificial intelligence-driven decision making. Inspired by works on AI applications in HRM, the scale concentrated on AI's role in strategic decision making, HR analytics and process automation (Tambe et al., 2019; Davenport & Ronanki, 2018). With Cronbach's $\alpha = 0.973$, the scale displayed great reliability, therefore reflecting a high degree of internal consistency.

This 10-item scale gauged workers' opinions on the moral questions and difficulties connected with artificial intelligence-based decision making. Inspired by past studies on AI governance and bias reduction, the items addressed areas including algorithmic bias, transparency, responsibility and ethical AI use (Binns, 2018; Rai et al., 2019). With Cronbach's $\alpha = 0.917$, the scale has shown great reliability, which means that it adequately reflects worries about how artificial intelligence influences organizational decision-making.

A 10-item subset of the International Personality Item Pool (IPIP) scale was used to gauge self-efficacy, that is, people's confidence in their capacity to control chores and problem-solving circumstances (Goldberg et al., 2006). Self-efficacy was included as a possible moderating factor since artificial intelligence-driven decision-making can affect employees' perception of control over HR operations. With a Cronbach's $\alpha = 0.944$, the scale showed great reliability, which supports its suit for evaluating self-efficacy in companies, including artificial intelligence.

Rational decision-making tendencies were measured on a 5-item scale, with reference to methodical, logical approaches to decision-making. The items were modified from the extensively referenced Scott & Bruce (1995) model of decision-making approaches. Considering how artificial intelligence improves data-driven decision making, this study looked at how employees' dependence on logical approaches interacted with AI application. With Cronbach's $\alpha = 0.933$, the scale showed great reliability, therefore showing remarkable internal consistency.

Measuring intuitive decision making, a complementing 5-item scale distinguished quick, experience-based judgment from data analysis. Also modified from Scott & Bruce (1995), the objects were used to investigate whether workers with a more intuitive decision-making style saw artificial intelligence differently than those using a logical approach. With Cronbach's $\alpha = 0.894$, the scale showed reasonable reliability, implying that it reasonably represents differences in decision-making preferences in HR environments supported by artificial intelligence. With Cronbach's $\alpha > 0.89$, all scales showed great internal consistency, therefore guaranteeing their fit to assess HRM AI integration and decision-making.

Analysis plan

To ensure the validity and reliability of the used measuring tools, the data analysis followed a methodical, multiphase methodology evaluating the link between artificial intelligence-driven decision-making and HR best practices. Integrated factorial validation, reliability testing, correlation analysis, network analysis and predictive modeling, the analytical method offers a whole picture of how artificial intelligence influences HRM.

Exploratory Factor Analysis (EFA) was used in the first phase to evaluate the underlying factorial structure of the HR Best Practices Scale (HRBPS) and associated scales related to AI. Given the expected intercorrelations between the HR dimensions, a Principal Axis Factoring (PAF) approach with Promax rotation was used. The Kaiser-Meyer-Olkin (KMO) test was used to assess the suitability of the sample; Bartlett's test of sphericity found whether the correlation matrix fit for factor extraction. Examined were factor loadings to make sure only objects significantly contributing to their respective constructions stayed with us. Cronbach's alpha coefficients were calculated after the EFA to evaluate the internal consistency validity of every scale, therefore guaranteeing that every measurement yielded consistent and replicable results.

The second step consisted of correlation analysis and descriptive statistics. The mean, standard deviation and range were among the descriptive statistics computed to compile participant responses across several HR and AI-related categories. Pearson's correlation analysis was used to investigate the relationships between HR practices and AI-driven decision-making execution. This study revealed the intensity of these links and whether use of artificial intelligence was noticeably correlated with recruiting, training, team communication and organizational culture.

Third-phase network analysis was done in order to investigate the structural links between artificial intelligence and HRM even more. Using a visual depiction of the relationships among the study variables, this analytical method helped to pinpoint critical nodes and important influencers within the AI-HR ecosystem. The study focused on centrality metrics including betweenness, proximity and strength to identify which HR factor was the most important in HR transformation led by artificial intelligence. Stronger links in the network revealed greater degrees of influence between HR sectors and artificial intelligence application.

Predictive modeling with decision tree regression was used in the last phase to investigate how AI-driven decision-making shapes HR best practices. The interpretability of the decision trees and their ability to capture intricate interactions between HR practices and AI adoption helped them to be chosen. To guarantee accuracy, the data set was divided into training and test sets. Multiple model evaluation metrics—Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and R^2—were computed to evaluate the accuracy and predictive power of the model.

Combining statistical validation with predictive modeling, this multiphase analytical method offered a complete assessment of how artificial intelligence affected HRM. Examining the factorial structure, correlation patterns, network relationships, and predicted results, the study sought to provide a complex picture of how artificial intelligence shapes HR best practices and decision-making processes.

Results and discussions

The study findings emphasize the degree to which AI integration predicts and influences HR processes, therefore providing insights on the link between AI-driven decision making and HR best practices. The results are arranged according to network analysis, factorial validation of the measuring scales, correlation analysis and predictive modeling applied with decision tree regression.

A decision tree regression analysis was done to investigate how management decision-making on HR best practices is. The interpretability of decision trees and their capacity to capture intricate, nonlinear correlations between HR factors and AI deployment helped to guide their choice. The random split of the data set into test (20%) and training (80%) sets guarantees a strong evaluation of the predictive performance of the model.

Comprising 232 observations in the training set and 57 in the test set, the model produced 55 decision splits.

Table 1. Feature importance

	Relative Importance
Employee familiarization with digital environment	**50.918**
AI experience	**27.535**
Best practices in human resources	**4.510**
Self-efficacy	**3.953**
Domain	**3.469**
Challenges of AI on the decision-making process	**3.297**
Gender	**3.081**
Intuitive decision	**2.305**
Rational decision	**0.580**
Job	**0.154**
Education	**0.127**
Age	**0.071**

Source: Authors' own research.

A feature importance analysis was performed (Table 1) in order to better grasp the factors guiding HR best practices in an environment driven by artificial intelligence. This study shows the relative contribution of every predictor variable in the decision tree regression model, thereby clarifying which factors most significantly affect the function of artificial intelligence in HR management.

With a relative relevance score of 50.918, employee familiarity with the digital environment shows to be the most significant predictor. This implies that workers more suited to digital tools and AI-powered HR systems are more likely to encounter successful AI-driven HR. The great influence of digital knowledge fits past studies stressing the need for technological adaptation in the acceptance of artificial intelligence (Bondarouk & Brewster, 2016). Companies trying to improve AI performance in HR should provide digital literacy initiatives and AI-related training as a top priority to guarantee seamless application.

With a relative value of 27.535, artificial intelligence experience was the second most important predictor. This result emphasizes how better personnel exposed to artificial intelligence systems are at applying AI-driven HR solutions. This outcome is consistent with earlier research showing that acceptance and use of artificial intelligence in corporate decision-making are much influenced by perceived AI competency (Jarrahi, 2018). Workers with little knowledge of artificial intelligence could find it difficult to properly combine AI technologies, implying a need for focused training programs that improve AI-related competencies at several professional levels.

With a relative value of 4.510, best practices in human resources show that current HR policies and systems somewhat influence artificial intelligence-driven HR deployment. Since they already have standardized recruitment, training and team management systems, companies with well-established HR practices could find it simpler to properly combine AI solutions. This underlines the need for human supervision in AI-driven HRM since it implies that artificial intelligence serves as a facilitator instead of a substitute for conventional HR policies.

Notable was also the function of self-efficacy (3.53), suggesting that employees' confidence in their own abilities shapes their capacity to connect with AI-powered HR systems. This is consistent with Bandura's (1997) self-efficacy hypothesis, which holds that those who have more confidence are more likely to adopt and make good use of new technology. The adoption of

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artificial intelligence in HRM might thus benefit from tailored assistance programs meant to increase employee self-efficacy in environments related to digital transformation.

Although less, the organizational domain (3.469) and the challenges of artificial intelligence in the decision-making process (3.297) also had influence. The little contribution of the organizational domain implies that, in some sectors as banking, technology and education, where AI adoption is already rather common, AI-driven HR strategies may be more successful. The difficulties with AI-based decision making, bias, openness issues, algorithmic responsibility, remain relevant in determining HR professionals' readiness to apply AI-driven methods (Binns, 2018).

Relative to demographic factors, gender (3.081), intuitive decision-making style (2.305) and rational decision-making style (0.580) had little effect on AI-driven HR outcomes. Although several research have indicated gender variations in technology adoption (Venkatesh et al., 2012), the comparatively modest significance of gender in this analysis suggests that experience and digital familiarity rather than demographic characteristics more significantly shape AI-related HR views. Similarly, intuitive or logical, decision-making approaches have no bearing on artificial intelligence-driven HR adoption, suggesting that objective skill sets rather than personal cognitive preferences define AI application in HRM.

Job role (0.154), education (0.127) and age (0.071) were the least important predictors; they imply that neither the professional level nor the educational background significantly influences the adoption of AI-HR. This result runs counter to some previous research showing that higher degrees of education predict more adoption of artificial intelligence (Marler & Fisher, 2013), although it might be a reflection of the growing availability of AI tools at many education and experience levels. Similarly, age had no impact, implying that generational variations have little effect on the adoption of artificial intelligence in HRM, supporting the view that training and artificial intelligence experience are more important than demographic factors in determining AI efficacy.

As shown in Figure 1, the decision tree exposes a hierarchical decision-making process in which the familiarity of the employee with the digital environment becomes the main determinant of the adoption of AI-driven decision-making. This conclusion supports earlier findings of the feature importance analysis, thus verifying that workers with higher degrees of digital literacy are more suited to make good use of AI solutions in HR operations.

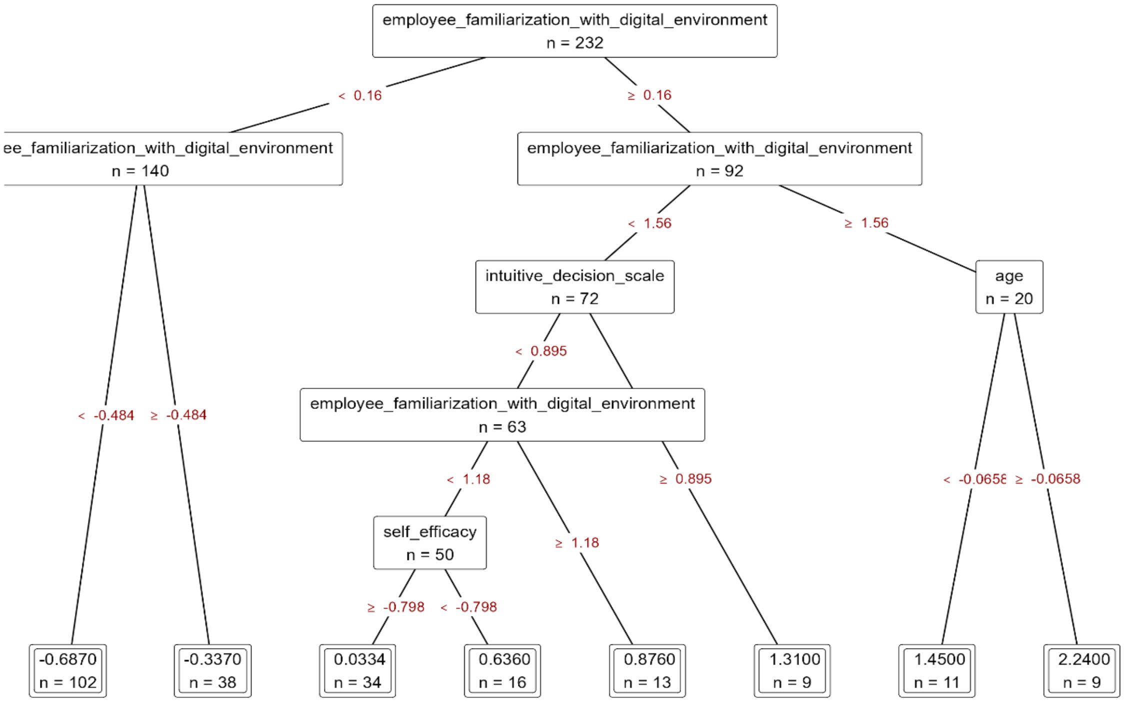

Figure 1. Decision Tree Plot

Source: Authors' own research.

With a threshold of 0.16, the decision tree separates the data set according to the knowledge of the employee of the digital environment in the first split. Higher digital familiarity people are therefore far more inclined to interact with AI-driven HR decision-making. Based on the terminal nodes on the leftmost branch of the tree, those with less familiarity typically have negative or worse AI engagement scores.

The second important predictor for those with greater digital awareness (≥ 0.16) is intuitive decision-making style, which adds another level of segmentation at 1.56. Lower in intuitive decision-making (< 1.56) employees often rely more on structured AI-driven procedures; those above 1.56 show more unpredictability in AI engagement, further influenced by age-related factors.

The tree branches even more to show more relationships with age and self-efficacy. For example, those with higher self-efficacy (≥ 1.18) demonstrate noticeably higher levels of AI adoption among employees with moderate digital knowledge and lower intuitive decision-making scores, therefore supporting the psychological function of confidence in AI-driven workplace change.

On the other hand, for workers with limited digital knowledge, the model finds a negative predictive trend in which participation in AI-driven decision-making declines dramatically (-0.686 for workers with lowest digital skills). This result emphasizes the important role digital literacy campaigns and artificial intelligence training programs play in closing the gap between workers and HR systems driven by artificial intelligence.

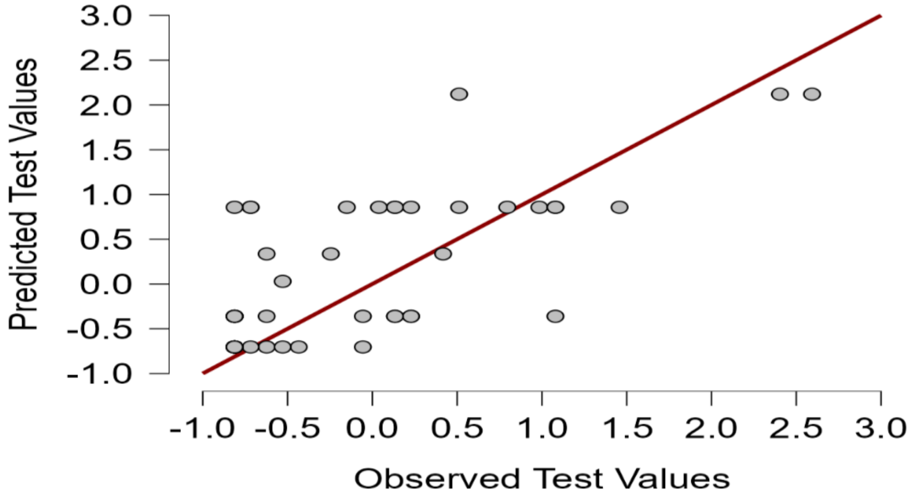

Figure 2. Predictive Performance Plot

Source: Authors' own research.

Figure 2 shows the Predictive Performance Plot, thus showing the ability of the decision tree regression model to forecast results depending on the chosen predictor variables, thus evaluating its predictive capacity. By means of a comparison between projected values and actual observed outcomes, this visualization is crucial in assessing the degree of generalization of the model to unseen data.

Multiple evaluation metrics—including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and R^2—coefficient of determination—were used to evaluate the predictive accuracy of the model. Based on the levels of AI implementation, the results revealed an MSE of 0.558, an RMSE of 0.747 and an MAE of 0.577, thus showing a modest degree of prediction error in determining HR best practices. The MAPE of 86.21% indicates that although the model offers important new perspectives on the interaction between artificial intelligence and HR, some prediction variance still exists.

With a R^2 value of 0.523, artificial intelligence-driven managerial decision making shows a modest predictive strength and suggests that around 52.3% of the variance in HR best practices may be explained by it. This result is consistent with current research, which implies that artificial intelligence is a major but not exclusive driver of HR practices, since other organizational, cultural and human factors influence HRM results (Tambe et al., 2019; Stone et al., 2015). Although this implies that several factors affect the adoption of artificial intelligence in HR, the decision tree emphasizes as the main determinants employee digital awareness, decision-making style and self-efficacy.

Furthermore, the hierarchical framework of the model implies that the adoption of artificial intelligence in HR is not homogeneous but depends on personal cognitive styles, confidence levels and industry-specific factors. Lower predictive values of demographic factors (such as age and education) confirm past results that skills and experience define AI integration more than variations in generational or academic background.

Discussions and limitations

In this paper, empirical data on the integration of artificial intelligence (AI) in human resource management (HRM) are presented, which, therefore, underlines its influence on HR best practices and decision-making procedures. The results highlight the need for digital familiarity and artificial intelligence experience among workers, as well as the need for ethical issues in artificial intelligence driven HRM.

Effective AI-driven HR practices are most strongly predicted by employee knowledge of the digital world, according to the data. This is consistent with previous studies stressing the need for technological flexibility in the acceptance of artificial intelligence inside HRM (Bondarouk & Brewster, 2016; Marler & Fisher, 2013). Workers who are skilled in digital tools are more suited to use artificial intelligence applications, thus improving HR operations. Similarly to studies stressing perceived AI competency as the main determinant of AI adoption in workplace decision making, AI experience emerged as a critical factor, suggesting that employees with greater exposure to AI systems are more adept at using AI-driven HR processes (Jarrahi, 2018; Tambe et al., 2019).

Furthermore, the function of self-efficacy in AI-HR interactions was important since employees' involvement with HR systems driven by AI depends on their trust in their own capabilities. This is consistent with Bandura's (1997) self-efficacy hypothesis, which holds that those who have more confidence are more likely to adopt and make good use of new technology. Therefore, companies should give AI-related training programs top priority since they not only raise employees' technical competency, but also increase their trust in using HR technologies driven by artificial intelligence (Davenport & Ronanki, 2018).

Although there are possible advantages, the integration of artificial intelligence into HRM poses various difficulties, especially in relation to algorithmic bias and openness. AI-driven judgments could inadvertently support prejudices in past HR data, therefore, fostering unfair hiring, promotion and assessment policies (Binns, 2018). To stop discriminatory results, companies must provide ethical audits of AI models and constant monitoring of them (Rai et al., 2019). Concerns about artificial intelligence explainability and fairness also force companies to create transparent policies that strike a mix between automation and human supervision, so ensuring that AI complements rather than replaces human knowledge in HR decision making (Stone et al., 2015; Van den Broek et al., 2021).

Although this work offers a detailed analysis, certain limits should be recognized. First, the cross-sectional character of the research limits the ability to deduce causality between artificial intelligence integration and HR results (Tambe et al., 2019). Future longitudinal research could provide a better understanding of how the adoption of artificial intelligence changes over time and its long-term effects on HR procedures.

Second, the study relied on self-reported data, which can be prone to social desiracle bias or erroneous self-assessment (Podsakoff et al., 2003). Including objective assessments of AI competency and use, such as system logs or HR analytics data, could improve the validity of next results.

Furthermore, the sample consisted of particular sectors and areas, which can influence the generalizability of findings in many other working environments. The adoption of artificial intelligence in HRM differs greatly between sectors; sectors such as finance and technology embrace AI more quickly than others, including healthcare or education (Marler & Fisher, 2013). Extensive knowledge of AI's involvement in HRM would come from future studies conducted in many geographic and business settings.

Building on the results of this study, the next studies should focus on longitudinal studies to evaluate how continual exposure to artificial intelligence-driven HR affects employee performance, engagement and organizational outcomes. Examining industry-specific AI adoption patterns might also provide insightful analysis of context-dependent best practices for the use of artificial intelligence in HRM (Jarrahi, 2018).

Understanding employee attitudes towards AI adoption in HRM is another crucial direction of future study. Although artificial intelligence can improve HR decision making, employee trust, perceived justice and acceptance will all determine its effectiveness (Venkatesh et al., 2012). Analyzing factors influencing trust in AI-driven decisions, including openness, ethical protections and user experience, may help to guide HR operations towards higher AI adoption (Davenport & Ronanki, 2018).

In particular in recruitment, performance reviews and staff retention tactics, future research should also investigate the interaction between AI-driven decisions and human judgment (Stone et al., 2015; Trifan et al., 2023). Research can present a more complex picture of the maximization of AI-human cooperation in workforce management by combining HR analytics, behavioral psychology, technology adoption theories and HR analytics.

Conclusions

This article clarifies how artificial intelligence (AI) is changing human resource management (HRM) and emphasizes the critical need for digital competency, AI experience and self-efficacy in making AI-driven HR practices successful. The findings imply that workers who are more familiar with digital tools and artificial intelligence technology are inevitably more involved with HR systems run under AI direction. This emphasizes the need for ongoing education and training programs to enable HR managers and staff members to adjust confidently to AI-driven technologies.

Although artificial intelligence (AI) offers HR efficiency, personalization and data-driven decision making, it also presents unavoidable difficulties such as algorithmic bias, ethical questions and transparency problems at the same time. The results highlight how artificial intelligence should be a strategic tool supporting improved HR decision making rather than replacing human knowledge. Organizations that strike this balance must guarantee robust human supervision to reduce ethical concerns, invest in AI-powered training programs and support fairness in AI-driven recruitment and evaluation.

Research on long-term effects, industry-specific issues and employee opinions of AI-driven procedures is obviously needed as artificial intelligence develops and shapes HRM in the future. By tackling these topics, companies can ensure that artificial intelligence is, instead of being a cause of uncertainty, a tool with inclusive, transparent and ethical responsibility. In the end, the possibilities of artificial intelligence in HRM will be fulfilled not just by technical development but also by careful application that respects the human experience as well as efficiency.

References

Abusweilem, M., & Abualoush, S. (2019). The impact of knowledge management process and business intelligence on organizational performance. Management Science Letters, 9(12), 2143-2156.

Alasmri, N., & Basahel, S. (2022). Linking artificial intelligence use to improved decision-making, individual and organizational outcomes. International Business Research, 15(10), 1-1.

Bandura, A. (1997). Self-efficacy: The exercise of control. W.H. Freeman.

Binns, R. (2018). Algorithmic accountability and public reason. Philosophy & Technology, 31(4), 543–556.

Bondarouk, T., & Brewster, C. (2016). Conceptualizing the future of HRM and technology research. The International Journal of Human Resource Management, 27(21), 2652–2671.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.

El Khatib, M., & Al Falasi, A. (2021). Effects of artificial intelligence on decision making in project management. American journal of industrial and business management, 11(3), 251-260.

Giraud, L., Zaher, A., Hernandez, S., & Akram, A. A. (2023). The impacts of artificial intelligence on managerial skills. Journal of Decision Systems, 32(3), 566-599.

Goldberg, L. R., Johnson, J. A., Eber, H. W., Hogan, R., Ashton, M. C., Cloninger, C. R., & Gough, H. G. (2006). The international personality item pool and the future of public-domain personality measures. Journal of Research in Personality, 40(1), 84–96

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577–586.

Kovačić, M., Mutavdžija, M., Buntak, K., & Pus, I. (2022). Using artificial intelligence for creating and managing organizational knowledge. Tehnički Vjesnik, 29(4), 1413-1418.

Marler, J. H., & Fisher, S. L. (2013). An evidence-based review of e-HRM and strategic human resource management. Human Resource Management Review, 23(1), 18–36.

Noponen, N. (2019). Impact of artificial intelligence on management. Electronic Journal of Business Ethics and Organization Studies, 24(2), 43-50.

Olan, F., Arakpogun, E. O., Suklan, J., Nakpodia, F., Damij, N., & Jayawickrama, U. (2022). Artificial intelligence and knowledge sharing: Contributing factors to organizational performance. Journal of Business Research, 145, 605-615.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903.

Rai, A., Constantinides, P., Sarker, S., & Trauth, E. (2019). Next-generation digital platforms: Toward human–AI hybrids. MIS Quarterly, 43(1), iii–ix.

Rajagopal, N. K., Qureshi, N. I., Durga, S., Ramirez Asis, E. H., Huerta Soto, R. M., Gupta, S. K., & Deepak, S. (2022). Future of business culture: An artificial intelligence-driven digital framework for organization decision-making process. Complexity, 2022(1), 7796507.

Rodgers, W., Murray, J. M., Stefanidis, A., Degbey, W. Y., & Tarba, S. Y. (2023). An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. Human Resource Management Review, 33(1), 100925.

Scott, S. G., & Bruce, R. A. (1995). Decision-making style: The development and assessment of a new measure. Educational and Psychological Measurement, 55(5), 818–831.

Shrestha, Y. R., Ben-Menahem, S. M., & Von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. California management review, 61(4), 66-83.

Stone, D. L., Deadrick, D. L., Lukaszewski, K. M., & Johnson, R. (2015). The influence of technology on the future of human resource management. Human Resource Management Review, 30(3), 100778.

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. California Management Review, 61(4), 15–42.

Trifan, V. A., Szentesi, S. G., Cuc, L. D., & Pantea, M. F. (2023). Assessing tax compliance behavior among romanian taxpayers: an empirical case study. Sage Open, 13(3), 21582440231195676.

Trunk, A., Birkel, H., & Hartmann, E. (2020). On the current state of combining human and artificial intelligence for strategic organizational decision making. Business Research, 13(3), 875-919.

Van den Broek, E., Sergeeva, A., & Huysman, M. (2021). When the machine meets the expert: An ethnography of developing AI for hiring. Organization Science, 32(1), 101–124.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2012). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.