JOURNAL OF CULTURAL ANALYSIS AND SOCIAL CHANGE

Journal of Cultural Analysis and Social Change,
2025, 10(3), 2720-2734
ISSN: 2589-1316

Applicability, Challenges and Barriers to the Implementation of Artificial Intelligence in Human Resource Management: A Multiple Moderation Model

Paola Sá[1], Rosa Rodrigues[2*]

[1] *Instituto Superior de Gestão - Business & Economics School, Lisbon, PORTUGAL*
[2] *CIGEST - Management Research Center, Lisbon, PORTUGAL*

***Corresponding Author:** rosa.rodrigues@isg.pt

Citation: Paola, S. & Rodrigues, R. (2025). Applicability, Challenges and Barriers to the Implementation of Artificial Intelligence in Human Resource Management: A Multiple Moderation Model, *Journal of Cultural Analysis and Social Change*, 10(3), 2720-2734. https://doi.org/10.64753/jcasc.v10i3.2828

Published: December 04, 2025

ABSTRACT

Understanding the factors that influence the future intention to use Artificial Intelligence (AI) in Human Resource Management (HRM) is essential to promote the effective adoption of these technologies in organisational settings. Based on a multiple moderation model, this study examined the role of perceived applicability of AI in HRM and the moderating effect of implementation challenges and barriers on future usage intention. A mixed-methods research design was adopted. In the first phase, interviews were conducted with 11 Human Resources (HR) professionals with experience in digital transformation processes. The qualitative analysis identified key thematic categories that informed the development of the survey questionnaire. In the second phase – a quantitative study – 157 questionnaires were administered to employees working with AI tools in HRM contexts. Statistical analysis revealed a direct and significant effect of the perceived applicability of AI on future usage intention. Additionally, the results indicated that perceived challenges positively moderate this relationship, strengthening the impact of applicability as implementation contexts become more demanding. In contrast, implementation barriers did not exhibit a significant moderating effect. These findings suggest that AI acceptance in HRM is more influenced by operational and strategic challenges than by structural barriers. It is concluded that recognising the applicability of AI, together with the organisational capacity to address internal challenges, is a key factor in professionals' predisposition to adopt such technologies in the future.

Keywords: Artificial Intelligence, Human Resource Management, Usage Intention, Organisational Challenges, Implementation Barriers, Multiple Moderation Model.

INTRODUCTION

Artificial Intelligence (AI) has taken on a central role in the digital transformation of organisations, increasingly influencing Human Resource Management (HRM) processes (Gao & Liu, 2023). Its application enables the automation of routine tasks, supports decision-making, personalises employee experiences, and enhances operational efficiency (Ijomah et al., 2024). These functionalities position AI as a strategic tool in the modernisation of HRM, helping to align organisational goals with the demands of an ever-evolving market environment (Al-Mamary et al., 2024).

Despite the high potential of AI in HRM, its adoption continues to display significant disparities (Fenwick et al., 2024). While some organisations adopt these technologies in a structured and consistent manner, others encounter structural obstacles that hinder their implementation (Khandelwal et al., 2024). This reality highlights that the intention to use AI in the future depends not only on the perception of its benefits but also on moderating factors that influence its implementation (Wongras & Tanantong, 2023).

Among the main obstacles are organisational challenges, such as resistance to change, the shortage of digital skills, and the complexity of technological integration (Zhang & Lee, 2025). These factors may act either as enablers or inhibitors, depending on how they are managed internally. Simultaneously, external or structural barriers – including implementation costs, lack of appropriate regulation, and ethical concerns – generate uncertainty about the feasibility and legitimacy of using AI in work settings (Ajunwa, 2025).

In this context, it becomes essential to understand the mechanisms that explain the relationship between the perceived applicability of AI and the intention to use it in the future, by analysing the moderating impact of challenges and barriers to its implementation. This approach captures the complexity of the phenomenon and provides empirical evidence on the factors that facilitate or hinder technological adoption in the HRM domain.

This study proposes a multiple moderation model that examines whether the perceived challenges and identified barriers condition the relationship between perceived applicability and the intention to use AI in the future. The model is theoretically grounded in the Technology Acceptance Model (TAM; Davis, 1989; Venkatesh & Davis, 2000) and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), by integrating contextual dimensions that are often overlooked in technology acceptance research.

By highlighting the conditional effects of AI applicability perceptions on future use intentions, this research contributes to advancing knowledge about the factors that sustain technological innovation in HRM.

LITERATURE REVIEW

Artificial Intelligence in Human Resource Management

AI has emerged as one of the most impactful technological innovations of the present era, with significant implications for organisational management, particularly in the field of HRM (Bersin, 2019). Its potential to transform practices, automate processes, and support decision-making has positioned AI as a key element in contemporary digital transformation strategies (Russell & Norvig, 2020). This evolution has been driven by the exponential growth of data storage and processing capabilities, enabling the real-time analysis of large data volumes (Kekevi & Aydin, 2022).

Broadly speaking, AI can be classified into two main types: (a) narrow AI, designed to perform specific tasks, such as CV screening or pattern recognition; and (b) general AI, aimed at simulating human intelligence across multiple domains (Triguero et al., 2023). In organisational contexts, AI applications have concentrated in five core areas: (a) process automation, where routine tasks are replaced by robotic systems (Chakraborti et al., 2020); (b) predictive analytics, based on identifying behavioural patterns from historical data (Yawar & Hakimi, 2025); (c) service personalisation in both internal and external marketing (Gao & Liu, 2023); (d) decision support, through algorithms that simulate scenarios and recommend actions (Ijomah et al., 2024); and (e) user interaction, notably via chatbots and virtual assistants (Sundari et al., 2024).

In HRM, AI integration has proven particularly valuable in areas such as recruitment and selection (R&S), onboarding, performance appraisal, and talent management and retention (Al-Mamary et al., 2024).

In recruitment, AI streamlines candidate screening, aligns profiles with job requirements, and analyses behavioural data gathered during digital interviews. Through machine learning techniques, algorithms can be trained using the history of successful professionals to predict the future performance of new candidates (Albassam, 2023).

During the onboarding process, AI contributes by automating administrative procedures, providing virtual assistants for FAQs, and personalising training actions (Ionescu et al., 2025). These features enhance integration, increase new hires' autonomy, and reduce the time needed to reach adequate performance levels (El Garem, 2024).

Performance appraisal has also benefited from AI, which enables the collection of data from multiple sources (e.g., supervisors, peers, subordinates), the analysis of behavioural patterns, and the delivery of real-time feedback (Nyathani, 2023). In contrast to traditional models based on periodic and subjective evaluations, AI offers a continuous, objective, data-driven approach (Bankar & Shukla, 2023).

In talent management, AI supports competency mapping, the identification of high-potential employees, personalised career planning, and the suggestion of internal mobility opportunities (Ong & Lim, 2023). By matching individual profiles with strategic organisational needs, these systems allow for more effective HR allocation and contribute to stronger retention outcomes (Maharaj & Obalade, 2025).

When applied to talent retention, AI helps predict turnover, identify risk factors such as dissatisfaction or lack of progression, and implement preventative measures – replacing reactive approaches with strategies centred on individual experience (Basnet, 2024).

Beyond its operational functionalities, AI enhances the strategic dimension of HRM by freeing HR professionals from repetitive tasks and enabling more analytical, consultative, and value-creating roles (Al-Mamary et al., 2024). Tools such as People Analytics and HR Intelligence make it possible to combine internal and external data, identify trends, and support evidence-based decision-making. These tools examine areas such as performance, organisational climate, motivation levels, and absenteeism patterns – anticipating risks and fostering more proactive action (Bersin, 2019).

The successful adoption of AI in HRM requires adequate organisational conditions, namely: robust technological infrastructures, digital maturity, continuous employee training, and clearly defined ethical principles (European Commission, 2019). Algorithm transparency and user trust are critical to AI acceptance (Tursunbayeva et al., 2021). In addition to technical skills, HR professionals must develop capabilities in data analysis, critical thinking, and holistic information interpretation. Within this new paradigm, HRM shifts from an administrative function to a strategic and cross-cutting role grounded in intelligent, ethical, and human-centred management (Adabala, 2025).

Future Intention to Use Artificial Intelligence in Human Resource Management

The intention to use AI-based technologies in HRM is shaped by a range of individual, organisational, and contextual factors. Key determinants include perceived usefulness, ease of use, trust in the technology, and its compatibility with organisational values and practices (Qamar et al., 2021). Together, these factors influence professionals' willingness to accept, adopt, and integrate AI solutions into their daily work processes (Khan et al., 2024).

Perceived usefulness refers to the extent to which users believe that the technology can enhance their job performance (Syaharani & Yasa, 2022). This expectation is often linked to the notion that AI improves efficiency, reduces errors, simplifies complex tasks, and delivers more reliable and faster results (Du, 2024). When professionals recognise that AI adds value to their work, they are more likely to adopt a positive attitude towards its use (Palos-Sánchez et al., 2022).

Ease of use relates to the perception that the technology is intuitive, accessible, and does not require excessive effort to use effectively (Bujold et al., 2024). In environments with low digital literacy, where employees may lack advanced technical skills, ease of use becomes even more important (Maharaj & Obalade, 2025). Interface simplicity, clear instructions, and seamless integration with existing systems are all factors that increase user acceptance (Ajunwa, 2025). The lower the cognitive effort required for learning, the greater the likelihood that employees will incorporate AI into their routines (Silva, 2024).

Trust in technology is essential for AI adoption, as employees must believe in its capacity to act fairly, impartially, transparently, and ethically (Du, 2024). Perceptions of algorithmic auditability, freedom from bias, and alignment with organisational fairness strongly influence the acceptance of AI (Yanamala, 2023). In HR contexts – where automated decisions directly impact individuals' careers (e.g., recruitment, performance evaluation) – trust is a fundamental requirement (European Commission, 2019).

Organisational culture also plays a critical role in shaping AI adoption intentions. Organisations that foster innovation, continuous learning, and efficiency are more open to experimenting with and integrating new technologies (Thilagavathy & Venkatasamy, 2023). Conversely, conservative or risk-averse cultures often exhibit greater resistance to AI, regardless of its potential benefits (Übellacker, 2025).

External pressures are also relevant, such as the need to keep up with industry trends, comply with legal requirements, improve performance indicators, or meet stakeholder expectations (Pedrami & Vaezi, 2025). Organisations operating in competitive and dynamic environments tend to perceive AI as a strategic tool for strengthening their market position and improving HR practices (Qamar et al., 2021).

The understanding of factors influencing AI usage intention is grounded in two widely recognised models: TAM and UTAUT. The TAM, developed by Davis (1989) and later refined by Venkatesh and Davis (2000), suggests that perceived usefulness and ease of use are primary predictors of technology adoption intentions.

The UTAUT, proposed by Venkatesh et al. (2003), expands this by incorporating social influence (e.g., peer pressure), facilitating conditions (e.g., available resources), and performance expectancy. This model has proven particularly effective in explaining the adoption of emerging technologies, including AI, across organisational contexts. It allows for a deeper understanding of individual motivations, organisational dynamics, and contextual constraints (Wongras & Tanantong, 2023).

The belief that AI can be integrated into HR practices is strongly linked to the intention to use it in the future (Qamar et al., 2021). When employees perceive AI as relevant, useful, easy to use, and aligned with their professional values, they are more likely to adopt it regularly (Palos-Sánchez et al., 2022).

Based on this theoretical background, the following hypothesis was formulated:

Hypothesis 1: *Perceived applicability of AI in HRM positively influences the intention to use it in the future.*

Perceived Challenges in Adopting Artificial Intelligence in Human Resource Management

The lack of digital skills in HR departments is one of the main obstacles to adopting AI-based technologies. Implementation requires an understanding of how these tools function and a clear awareness of their potential and limitations in managing people (Zhang & Lee, 2025). This necessity highlights the importance of investing in the upskilling of HR professionals, whose academic background is often rooted in the social sciences and humanities (Bersin, 2019). Without this knowledge, HR practitioners become dependent on others, reducing their autonomy and strategic contribution to effective AI integration in HRM (Taslim et al., 2025).

Technical unpreparedness diminishes employee engagement, hinders acceptance of new technologies, and limits their full potential (Sakka et al., 2022). In low digital literacy environments, AI is often perceived as a threat to job stability or as a tool that depersonalises HR functions (Han, 2024). Overcoming this challenge requires practical training programmes that are accessible, tailored to employee profiles, and delivered in clear language (Sundari et al., 2024). Collaboration between HR and IT professionals also helps foster a more open organisational culture toward knowledge sharing and digital innovation (Fenwick et al., 2024).

In addition to training, leadership must take a strategic stance on the role of digital skills in transforming HR departments. Professional requalification should be seen as a continuous adaptation process to new technological demands, playing a central role in organisational change (Sundari et al., 2024). As Han (2024) highlights, digital transformation cannot occur without empowering those responsible for managing human capital.

AI effectiveness depends on its real-time integration with other digital platforms, such as recruitment software, performance appraisal systems, employee databases, and business intelligence tools (Halid et al., 2024). Yet many organisations still rely on outdated, incompatible, or isolated systems, which undermine technical integration and limit coordination across tools (Khandelwal et al., 2024). This technological complexity can frustrate users, especially when AI solutions are introduced without adequate preparation, compatibility guarantees, or clear explanations of their functionalities (Simkute et al., 2024). When perceived as intrusive, unnecessary, or difficult to use, AI tools are often rejected, even when users acknowledge their potential to improve processes (Pedrami & Vaezi, 2025). Effective implementation requires a progressive and integrated approach, including the definition of strategic goals, operational priorities, and realistic, sustainable plans. A phased rollout helps reduce resistance and gradually increase user acceptance (Vishwakarma & Singh, 2023).

Addressing the challenges of implementing AI in HRM demands an organisational approach based on three core pillars: (a) transparent internal communication that clarifies the objectives, benefits, and limitations of the technology (Prikshat et al., 2023); (b) employee involvement in the selection, adaptation, and monitoring of tools, ensuring their feedback and concerns are considered (Khan et al., 2024); and (c) positioning AI as a support tool for human intelligence, rather than a threat or replacement (Ijomah et al., 2024). The way these challenges are perceived, communicated, and managed directly influences the assessment of AI applicability and, consequently, the intention to use it in the future (Qamar, 2021). Perceived challenges can act as change catalysts, provided they are addressed through structured organisational responses and inclusive participation (Prikshat et al., 2023).

Based on this understanding, the second research hypothesis was formulated:

Hypothesis 2: *Perceived challenges in implementing AI positively moderate the relationship between its perceived applicability and the intention to use it in the future.*

Barriers to Implementing Artificial Intelligence in Human Resource Management

AI adoption in HRM faces various barriers that hinder its implementation. Among the most significant are the shortage of professionals with specialised technical skills, high financial costs, and ethical and legal concerns surrounding the use of automated systems (Fenwick et al., 2024).

The lack of qualified personnel limits the ability to participate actively in the selection, adaptation, and monitoring of AI tools (Han, 2024). The absence of internal expertise impairs the definition of technical and ethical criteria necessary to ensure responsible technology use (Maharaj & Obalade, 2025). When HR professionals lack digital proficiency, it becomes harder to guarantee organisational justice, equal opportunity, and personal data protection (Abaas & Robbins, 2024).

Financial costs also represent a major obstacle, since beyond the initial investment in software, infrastructure, and technical consultancy, continuous training and technical support are required (Khan et al., 2024). These expenses are particularly challenging for small and medium-sized enterprises with limited budgets (Oni, 2025). Without proper financial planning, AI projects often fail due to lack of sustainability or return on investment (Sithambaram & Tajudeen, 2023).

Implementing AI may also require internal process reorganisation, contract renegotiation, and adaptation of complementary systems. These indirect costs, although less visible, are significant and must be considered from a holistic perspective (Oni, 2025). The absence of a strategic vision compromises both continuity and employee trust in innovation initiatives (Fenwick et al., 2024). Organisations should therefore develop cost–benefit models to support implementation (Mashudi et al., 2025).

Ethical and legal concerns also constitute a critical barrier. Mass data collection raises issues regarding privacy, data protection, and algorithm transparency (Mirishli, 2025). Many AI tools may undermine fairness and accountability, particularly when used in HR processes that significantly impact employees (e.g., promotions, evaluations; European Commission, 2019).

There is also a risk of algorithmic discrimination, as biased training data can reproduce or even amplify structural inequalities, disproportionately affecting vulnerable groups (Ferrara, 2024). As An et al. (2024) note, discriminatory outcomes based on gender, age, or ethnicity have been reported in AI-supported recruitment processes, undermining workplace fairness and equity.

Furthermore, the lack of specific regulations governing AI in the workplace increases legal uncertainty and discourages adoption (Almeida, 2023). According to Ajunwa (2025), many organisations hesitate to use these technologies due to concerns about legal compliance and potential violations of workers' rights. These ethical and legal concerns influence the acceptance of AI by both HR professionals and employees (Fenwick et al., 2024). Overall, the implementation of AI in HRM is constrained by barriers that may attenuate the positive impact of perceived applicability on future use intentions.

Based on this evidence, the third research hypothesis was proposed:

Hypothesis 3: *Perceived barriers to implementing AI negatively moderate the relationship between its perceived applicability and the intention to use it in the future.*

Figure 1 illustrates the relationship between the study variables and the corresponding research hypotheses.

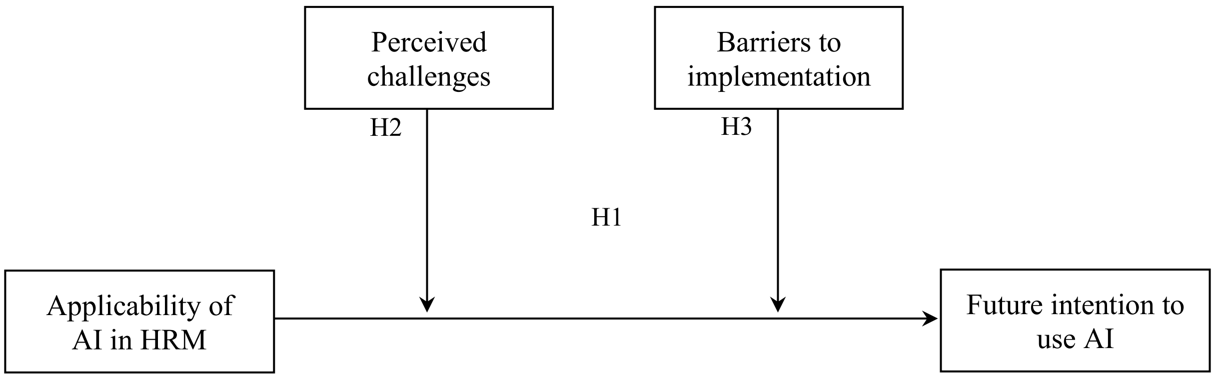

Figure 1. Multiple moderation model of perceived challenges and barriers to AI implementation in the relationship between its applicability in HRM and future use intention
Source: Authors' own work
Note: To avoid overloading the figure and to enhance clarity, the variables "Perceived Challenges" and "Barriers to Implementation" refer respectively to challenges perceived during AI implementation in HRM and to organisational-level barriers that hinder such implementation.

The literature review enabled the identification of key challenges and barriers to implementing AI in HRM, as well as the main factors influencing future intention to use this technology.

METHODOLOGY

Research Design

This study adopted a sequential exploratory mixed-method design, combining qualitative and quantitative data collection and analysis. The qualitative phase was conducted first and served as the foundation for developing the quantitative instrument. The goal was to ensure that the questionnaire dimensions reflected the real-world experience of HR professionals regarding AI use in organisations. This type of design is particularly suitable when exploring phenomena that are not yet well established theoretically, as it allows for a bottom-up approach in operationalising constructs that can later be quantified (Creswell & Clark, 2018).

Qualitative Study: Exploratory Interviews

The main objective of the qualitative phase was to gain an in-depth understanding of HR professionals' perceptions regarding AI use in HRM, the challenges faced, implementation barriers, and expectations about future adoption. The insights gathered were essential for developing the dimensions and indicators later used in the questionnaire.

Participants

A total of 11 HR professionals in managerial or coordination roles (e.g., HR Business Partner, HR Manager) were interviewed. All had several years of experience with organisational digital transformation processes (Min =

7; Max = 28; M = 15.27; SD = 7.89). Participants were selected through convenience sampling. The average age was approximately 38 years (Min = 30; Max = 51; M = 38.27; SD = 8.37), and 54.6% were male. Notably, 72.7% of the participants worked in small and medium-sized enterprises (SMEs).

Qualitative Data Collection Instrument

Data were collected using a semi-structured interview guide composed of four questions, specifically designed for this study and grounded in the literature review (e.g., Bujold et al., 2024; Palos-Sánchez et al., 2022; Qamar et al., 2021; Vrontis et al., 2021).

The first question addressed the use of AI in HRM and aimed to assess whether organisations were applying such technologies at strategic and/or operational levels.

The second question explored the main challenges faced during AI implementation, with particular attention to internal resistance, employee adaptation difficulties, and how these challenges were managed.

The third question focused on organisational barriers to AI adoption in HRM, aiming to identify reasons that have limited or prevented the integration of these technologies — even where there was interest or need. This included issues such as lack of specialised human resources, resistance to change, ethical concerns, and associated costs.

Lastly, the fourth question investigated future intention to use AI in HRM, seeking to understand the motivations or reasoning behind this intention, including perceived usefulness, trust in outcomes, and expected return on investment. These questions formed the basis for the item construction in the subsequent survey.

Procedures

The interviews were conducted via Zoom and lasted approximately 20 minutes. All participants were informed of the study objectives and signed a digital informed consent form, authorising the recording and later analysis of the interviews. The research received ethical clearance from the ISG/CIGEST Ethics Committee, confirming that it adheres to the established ethical principles for studies involving human subjects. This authorisation highlights the study's dedication to safeguarding participants' privacy, securing informed consent, and ensuring that participation was entirely voluntary.

The content analysis followed Bardin's (2016) recommended steps: (a) pre-analysis; (b) data exploration; and (c) analysis, inference, and interpretation. This procedure enabled the identification of response patterns and the categorisation of themes that were later used to construct the variables included in the survey. Data analysis was conducted using MAXQDA software.

Quantitative Study: Survey

The quantitative phase involved the administration of a questionnaire to employees from various organisations with different levels of digital maturity in HRM. A total of 176 questionnaires were distributed using a non-probability sampling approach. However, only 157 were deemed valid, as 19 respondents indicated they had no experience with AI tools in their organisational context – an essential criterion for inclusion in this study.

Participants

The final sample consisted of 157 participants, the majority of whom were male (59.8%). The average age was approximately 41 years (SD = 9.94; Min = 20; Max = 60). The respondents' sociodemographic characteristics are presented in Table 1.

Table 1. Sample Characteristics

Variables	N = 157
Gender (as stated on ID document)	
Male	94 (59.8%)
Female	63 (40.2%)
Age group (M = 41.23; SD = 9.94; Max =60; Min = 20)	
Less than or equal to 30 years	43 (27.3%)
Between 31 and 40 years	47 (29.9%)
Between 41 and 50 years	45 (28.6%)
Greater than or equal to 51 years	22 (14.2%)
Education level	
Secondary education	29 (18.5%)
Bachelor's degree	86 (54.7%)
Master's degree	42 (26.8%)
Professional experience (M = 7.68; SD = 3.86)	
Less than or equal to 5 years	52 (33.1%)
Between 6 and 10 years	63 (40.2%)

Greater than or equal to 11 years	42 (26.7%)
Company size	
Small (10 to 49 employees)	39 (24.8%)
Medium (50 to 249 employees)	71 (45.3%)
Large (250 or more employees)	47 (29.9%)
Years of using AI in HRM (M = 3.70 years; SD = 1.86)	
Less than or equal to 2 years	70 (44.5%)
Between 3 and 5 year	56 (35.7%)
Greater than or equal to 6 years	31 (19.8%)
Digital maturity	
Developing	78 (49.6%)
Advanced	62 (39.5%)
Highly advanced	17 (10.9%)

Source: Authors' own work

Quantitative Data Collection Instrument

The questionnaire was developed based on the results from the qualitative phase (interviews) and supported by studies conducted by Bersin (2019), Chui et al. (2016), Russell and Norvig (2016), and Venkatesh and Davis (2000). Accordingly, 16 items were created and grouped into four key dimensions: (a) AI application in HRM (4 items; e.g., *The organisation where I work uses AI tools in recruitment and selection processes*); (b) perceived challenges in implementing AI in HRM (6 items; e.g., *The organisation where I work faces difficulties in implementing AI in HRM due to a lack of specialised technical skills in this area*); (c) barriers to AI implementation in HRM (4 items; e.g., *Lack of awareness about AI's potential hinders its integration in HRM*); and (d) future intention to use AI in HRM (2 items; e.g., *The organisation where I work intends to expand the use of AI-based tools in HRM*).

All responses were recorded on a five-point Likert scale ranging from 1 ("Strongly disagree") to 5 ("Strongly agree").

The internal consistency of the scales was assessed using Cronbach's alpha, with results indicating acceptable reliability (AI applicability in HRM: $\alpha = 0.76$; Perceived challenges: $\alpha = 0.84$; Barriers to implementation: $\alpha = 0.78$; Future intention to use: $\alpha = 0.76$), all above the 0.70 threshold recommended by Hair et al. (2019).

Procedures

The questionnaire was made available online via Google Forms and disseminated through email and the researcher's professional networks (e.g., LinkedIn) between March and April 2025. Participation was voluntary and anonymous. Data confidentiality and compliance with ethical standards for research involving human subjects were ensured. All participants were informed in advance about the study's objectives. Data analysis was conducted using SPSS (version 29) and AMOS (version 29).

RESULTS

The presentation of results follows the sequence outlined in the methodology. First, the findings from the qualitative approach are reported, followed by the analysis of the quantitative data.

Qualitative Analysis

The qualitative analysis provided insight into HR professionals' perceptions of AI's relevance in organisational contexts, while also identifying the main challenges and barriers associated with its implementation. This approach enabled a deeper understanding of the role AI tools play in transforming people management processes.

Although the number of participants was limited, four thematic categories were identified, reflecting key trends and concerns surrounding the implementation of AI-based tools (Table 2).

Table 2. Thematic Categories

Main Categories (Conceptual)	Intermediate Categories (Axial)
Application of AI in HRM	▪ Process efficiency and optimisation ▪ Decision-making support ▪ Digital transformation ▪ Automation of repetitive tasks
Perceived challenges in implementing AI in HRM	▪ Resistance to change ▪ Need for training ▪ Technological challenges
Barriers to AI	▪ Lack of specialised human resources

implementation in HRM	▪ Associated costs ▪ Ethical concerns ▪ Technological integration
Intention to use AI in HRM in the Future	▪ Expand usage ▪ Maintain current usage

Source: Authors' own work

The first question focused on the relevance that interviewees attributed to the use of AI-based systems in the HRM domain. The majority (73.0%) highlighted their contribution to process efficiency, evidence-based decision-making, and increased agility, as illustrated by the following excerpts:

"*AI has accelerated processes such as recruitment and performance appraisal, which gives us more time to focus on tasks that require greater human involvement. This has been crucial for improving the department's overall efficiency.*"

"*With AI, we have been able to identify behavioural patterns that previously went unnoticed. It has proven useful for anticipating turnover and implementing preventive measures, which directly contributes to talent retention*."

When asked about the main challenges encountered during AI implementation in HRM, 43.5% of interviewees mentioned team resistance to change, 34.8% cited the lack of adequate training, and 21.7% identified difficulties related to system integration. These findings indicate that the obstacles are largely human and organisational in nature, thus requiring a strategic and participative approach. The way these challenges were perceived and addressed is reflected in the following statements:

"*There was some initial resistance from employees, especially those who were more accustomed to manual processes. It was essential to communicate that AI was not here to replace anyone, but rather to support everyone's work*."

"*The main challenge was the lack of digital skills within the team. We had to invest in training and awareness-raising to ensure everyone understood how to use the tools effectively*."

The third question aimed to identify the barriers that have hindered or prevented the adoption of AI in HRM. All respondents acknowledged the existence of relevant obstacles, particularly the lack of qualified technology professionals (35.2%), resistance to change (26.7%), implementation costs (22.2%), and ethical concerns (15.9%). These barriers have affected the pace and scope of AI adoption, even in contexts where there is interest and openness to exploring its potential. These perceptions are reflected in the following accounts:

"*One of the main bottlenecks is the difficulty in finding professionals with the technical skills to work with AI. Without the right support, it becomes complicated to integrate these tools effectively*."

"*Despite strong interest from top management, implementation costs are still seen as a barrier – especially in medium-sized companies*."

Finally, HR professionals were asked about their intention to use AI in HRM in the future. The findings revealed that 55.4% intend to expand the use of this technology, 27.4% plan to maintain current levels of use, and 17.2% have not yet defined a clear strategy. This trend toward expansion suggests a positive perception of AI's impact, linked to its practical utility, result reliability, and potential return on investment. These views were further supported by the following quotes:

"*AI has helped us make quicker, more informed decisions. For that reason, we want to extend its application to other HRM areas, such as training and performance evaluation*."

"*At the moment, we are satisfied with how we use AI, but we are keeping an eye on new market solutions. If a more integrated tool becomes available, we may revise our strategy*."

The qualitative analysis provided insight into HR professionals' perceptions, expectations, and constraints in adopting AI. The responses revealed a predominantly favourable view of AI integration in HRM, acknowledging its contribution to organisational efficiency, process personalisation, and enhanced decision-making. Nonetheless, significant technical, human, and ethical challenges were also identified, which hinder full-scale implementation.

The intention expressed by the majority of participants to expand AI use reinforces the notion that this technology is perceived as a strategic tool — provided it is supported by adequate investment and training. These insights served as the foundation for the development of the quantitative survey instrument, which was subsequently administered to a broader group of employees. The following section presents the results of this analysis.

Quantitative Analysis

Based on the thematic categories identified in the qualitative phase, a questionnaire was developed to collect data from employees. The purpose of the quantitative approach was to empirically test the relationships proposed in the conceptual model through regression and moderation analyses. The hypotheses aimed to examine: (a) the influence of perceived AI applicability on future use intention; and (b) the moderating role of perceived challenges in AI implementation in HRM and perceived barriers encountered during this process.

Hypothesis 1, which posited that perceptions regarding the application of AI in HRM processes positively influence the intention to use it in the future, was supported. The results revealed a positive and statistically significant effect between the predictor variable and the outcome variable (β = 0.159, $p < 0.05$). These findings indicate that the more positive the perception of AI applicability in HRM processes, the greater the employees' intention to use it in the future.

The moderating effect of perceived challenges in AI implementation in HRM and barriers to implementation was tested using Model 2 of the PROCESS macro for SPSS (version 4.0; Hayes, 2018). This analysis allowed for the simultaneous examination of two moderator variables on the relationship between the independent and dependent variables. To enhance the statistical accuracy of the results, a 95% confidence interval was estimated based on 5,000 bootstrap samples with bias correction, as recommended by Hayes (2018).

The results showed that perceived challenges positively moderate the relationship between AI applicability in HRM and future intention to use it, strengthening the positive effect of applicability as the level of perceived challenges increases. The interaction analysis suggests a moderating effect of small magnitude, but nonetheless statistically significant.

Table 3 presents the conditional effects of AI applicability in HRM on the intention to use it in the future, according to the levels of perceived challenges. When perceived challenges are low, the effect is positive and statistically significant (B = 0.143, $p < 0.05$, 95% CI [0.035, 0.322]). The confidence interval does not include zero, which reinforces the statistical robustness of the result. Under moderate levels of perceived challenges, the effect increases (B = 0.219, $p < 0.05$, 95% CI [0.083, 0.354]), indicating that the relationship between AI applicability in HRM and future use intention becomes stronger as the challenges intensify. Finally, when challenges are perceived as high, the effect remains statistically significant and reaches its highest value (B = 0.295, $p < 0.05$, 95% CI [0.117, 0.472]).

These results suggest that, regardless of the intensity of perceived challenges, the perception of AI applicability in HRM is consistently associated with greater future intention to adopt the technology, thereby confirming Hypothesis 2. Moreover, the progressive increase in regression coefficients indicates that the more demanding the implementation context, the greater the recognition of AI's potential – which may, in turn, enhance its future acceptance.

Table 3. Conditional effects of AI applicability in HRM on future use intention, based on levels of perceived challenges during implementation

Level of perceived challenges	Effect (B)	Standard Error (SE)	p-value	95% CI [LLCI, ULCI]
Low	0.143	0.050	0.011	[0.035, 0.322]
Medium	0.219	0.068	0.002	[0.083, 0.354]
High	0.295	0.090	0.001	[0.117, 0.472]

Source: Authors' own work
Note: B = unstandardised regression coefficient; SE = standard error; 95% CI [LLCI, ULCI] = 95% confidence interval, with lower (LLCI) and upper (ULCI) limits

Figure 2 illustrates this moderation effect. The results indicate that when perceived challenges are high, the effect of AI applicability in HRM on future intention to use it becomes stronger. In contrast, when challenges are perceived as low, the impact of AI applicability on future use intention is less pronounced. This interaction suggests that perceived challenges act as a strengthening factor in the relationship between perceived applicability and the intention to adopt AI in the future.

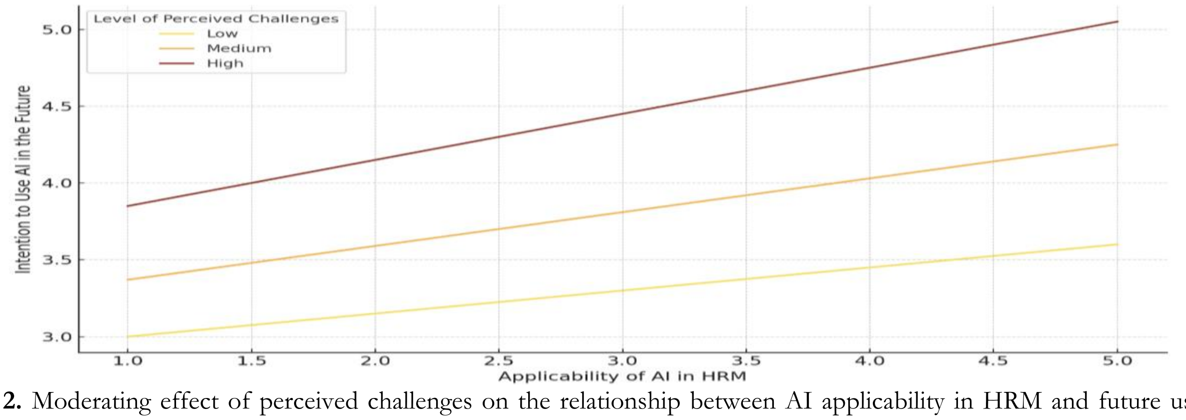

Figure 2. Moderating effect of perceived challenges on the relationship between AI applicability in HRM and future use intention
Source: Authors' own work
Note: The interaction is statistically significant, indicating that the impact of AI applicability on the intention to use is stronger in contexts where higher levels of perceived challenges are present.

In contrast, barriers to AI implementation in HRM did not exhibit any significant effect, either as a direct predictor ($p = 0.877$) or as a moderator of the relationship between AI applicability and future use intention ($p = 0.590$). This absence of effect may be explained by the nature of the perceived barriers, which may not be sufficiently prohibitive to alter the underlying mechanisms influencing future usage intentions.

Table 4 presents the conditional effects of perceived AI applicability in HRM on the intention to use it in the future, across different levels of perceived implementation barriers. The analysis shows that in contexts with low (B = 0.095, $p = 0.248$), medium (B = 0.102, $p = 0.194$), and high (B = 0.109, $p = 0.203$) levels of barriers, the effects are not statistically significant. In all cases, p-values exceed the conventional threshold of 0.05, and the confidence intervals include zero.

These results suggest that the perception of barriers to AI implementation does not significantly moderate the relationship between AI applicability and future use intention. Consequently, Hypothesis 3 was not supported. The lack of a moderating effect may indicate that, regardless of existing barriers, professionals do not perceive them as obstacles capable of undermining the potential of AI in the HRM context.

Table 4. Conditional effects of AI applicability in HRM on future use intention, according to levels of perceived implementation barriers

Level of perceived barriers	Effect (B)	Standard Error (SE)	p-value	95% CI [LLCI, ULCI]
Low	0.095	0.081	0.248	[-0.065, 0.256]
Medium	0.102	0.078	0.194	[-0.052, 0.257]
High	0.109	0.085	0.203	[-0.059, 0.277]

Source: Authors' own work
Note: B = unstandardised regression coefficient; SE = standard error; 95% CI = 95% confidence interval, with lower (LLCI) and upper (ULCI) limits

Figure 3 illustrates the moderating effect of perceived barriers on the relationship between AI applicability in HRM and the intention to use it in the future. The visual inspection of the interaction plot reveals that the slopes for low, medium, and high levels of perceived barriers are almost parallel and closely aligned. This pattern suggests the absence of a meaningful moderating effect. In other words, regardless of whether the perceived implementation barriers are low or high, the positive association between the perceived applicability of AI and the intention to use it remains largely unchanged.

This visual pattern confirms the lack of statistical significance observed in Table 4. Unlike internal challenges, external barriers to AI implementation, such as costs, ethical concerns, or the shortage of specialised professionals, do not appear to substantially alter the relationship between perceived AI applicability and the intention to use it in the future.

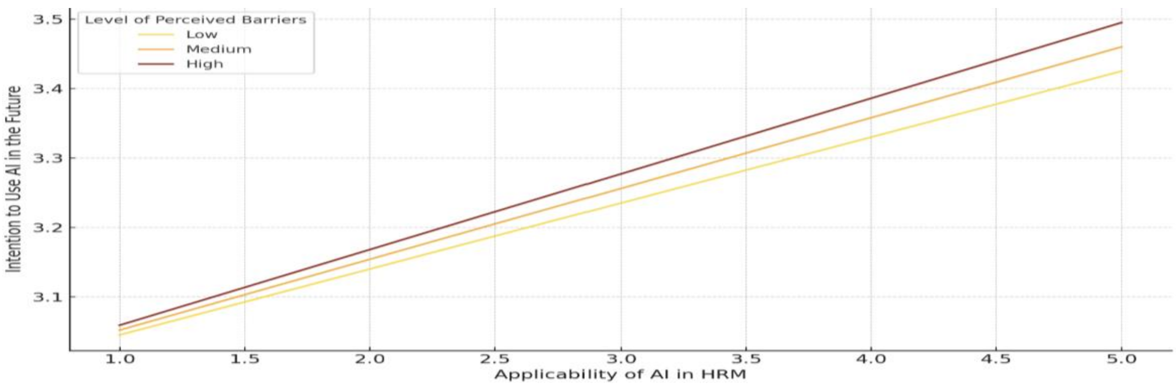

Figure 3. Moderating effect of perceived barriers on the relationship between AI applicability and future use intention
Source: Authors' own work
Note: The parallel lines suggest the absence of a statistically significant moderating effect.

Quantitative analysis confirmed the theoretical model only partially. It revealed a direct and positive effect of AI applicability in HRM on the intention to use it in the future. This result reinforces the relevance of AI as a driver of innovation and organisational efficiency. In addition, the moderation analysis indicated that perceived challenges in implementing AI act as a significant moderator of this relationship, intensifying the positive effect of applicability, particularly in contexts perceived as more demanding.

In contrast, perceived barriers to AI implementation did not show any significant interaction effect and thus did not moderate the relationship under analysis. These findings suggest that employees' willingness to adopt AI solutions is more sensitive to strategic and operational challenges than to external or structural barriers. As such, the study offers relevant contributions to both research and practice by highlighting the importance of change management and perceived applicability in fostering future technology adoption behaviours.

DISCUSSION OF FINDINGS

This study sought to investigate the influence of AI applicability on the intention to use it in the future, while also exploring the moderating role of challenges and barriers to its implementation in HRM. The quantitative analysis confirmed Hypothesis 1, revealing a direct and statistically significant relationship between perceived AI applicability and future use intention. This finding aligns with the TAM, which posits that perceived usefulness is a primary predictor of technology adoption (Venkatesh & Davis, 2000).

Building on this premise, Qamar et al. (2021) argue that the perceived compatibility of AI with organisational values and practices significantly enhances future adoption intentions. Similarly, Palos-Sánchez et al. (2022) demonstrate that the more professionals perceive AI as useful, the more inclined they are to adopt it. Syaharani and Yasa (2022) further found that the expectation of performance improvement fosters favourable attitudes towards AI use in different organisational settings. Du (2024) adds that perceptions of applicability are directly linked to trust in the technology and perceived return on investment, both of which reinforce adoption intentions.

Hypothesis 2 was also supported, as higher levels of perceived challenges strengthened the relationship between AI applicability and intention to use it in the future. This suggests that in more demanding contexts, the perceived usefulness of AI is more highly valued and recognised. As noted by Prikshat et al. (2023), challenge perception can trigger a proactive attitude, enhancing technology acceptance. According to Khan et al. (2024), when well managed, challenges stimulate skill development and accelerate teams' digital maturity. This is consistent with Sundari et al. (2024), who emphasise the importance of ongoing training and strategic leadership in the digital transformation of HRM. Thus, operational, technological, or human challenges may reinforce the perceived strategic value of AI, as evidenced by this study and corroborated by Zhang and Lee (2025).

The results also showed that barriers to AI implementation had no significant effect, either as a moderator or direct predictor of future usage intention, resulting in the rejection of Hypothesis 3. Although the literature points to numerous barriers – such as lack of technical skills (Han, 2024), financial constraints (Khan et al., 2024), ethical risks (An et al., 2024), and lack of regulation (Ajunwa, 2025) – these factors do not appear to significantly affect AI adoption when the technology is perceived as useful and applicable. Ferrara (2024) argues that perceived barriers can be mitigated when strong beliefs exist about AI's strategic benefits. Similarly, Oni (2025) suggests that even in resource-constrained settings, perceived usefulness often outweighs structural limitations. Übellacker (2025) further proposes that some barriers are too abstract to influence immediate decision-making. Additionally, as noted by Maharaj and Obalade (2025), when AI is positioned as a tool that supports rather than replaces human intelligence – with transparency and fairness guarantees – resistance tends to diminish.

These findings deepen our understanding of the factors that influence future AI usage in HRM. The partial validation of the theoretical model highlights the central role of perceived applicability in shaping adoption intentions, especially in operationally or strategically challenging environments. Conversely, the lack of significant effects for perceived barriers suggests that external or structural constraints may have less impact than previously assumed, reinforcing the importance of internal perceptions and organisational dynamics in technology acceptance processes.

Theoretical and Practical Contributions

This study contributes to the advancement of scientific knowledge on the adoption of AI in HRM by proposing and empirically validating a multiple moderation model that integrates variables often overlooked in technology acceptance research. The combined analysis of perceived AI applicability, perceived challenges, and barriers to its implementation provides a more robust understanding of the factors influencing future use intentions of this technology in organizational settings.

From a theoretical perspective, the main contribution lies in the extension of classical technology acceptance models – namely TAM and UTAUT – through the inclusion of contextual moderating variables. While these models typically explain technological adoption based on constructs such as perceived usefulness and ease of use, they rarely account for the organizational, technical, and human constraints that affect practical implementation. By incorporating perceived challenges and barriers as moderating variables, this research offers a more comprehensive and realistic view of the factors that influence technology adoption behavior among HR professionals.

Contrary to expectations, challenges did not act as inhibitors but rather enhanced the perceived value of AI applicability, thereby strengthening the intention to adopt it in the future. This finding challenges the traditional view that obstacles hinder AI adoption and suggests that, when difficulties are effectively managed, they can stimulate change – provided that appropriate leadership, internal communication, and digital upskilling strategies are in place. Conversely, the absence of a moderating effect from structural barriers – such as cost, lack of qualified personnel, or ethical concerns – suggests that while these factors are acknowledged, they do not significantly compromise the intention to adopt AI in the future. This insight opens new avenues for research into the mechanisms of organizational rationalization and resilience that help mitigate the impact of external constraints on technology adoption decisions.

From a practical standpoint, this study offers guidance for decision-makers and HR managers aiming to implement AI-based technologies effectively. It also highlights the importance of investing in the technical training of professionals so they can use these tools in a conscious, ethical, and efficient manner. The empirical evidence can support those responsible for digital transformation in building compelling arguments for top management, by demonstrating that perceived AI applicability is a central predictor of future acceptance and adoption.

Furthermore, the results suggest that managing internal challenges may be more decisive than overcoming structural barriers. This insight is particularly relevant for small and medium-sized enterprises, which, despite budget constraints, can drive technological innovation if they successfully mobilize their human resources and leadership around a shared vision of transformation.

The study contributes to building a more integrated and realistic framework for understanding AI adoption in HRM, with significant implications for both academic research and organizational practice. The proposed model serves as a solid foundation for future research and a practical tool for guiding strategic interventions in the field of technological innovation in HR.

STUDY LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Despite its theoretical and practical contributions, several limitations must be acknowledged, as they affect the generalizability of the findings and should be taken into account when interpreting the data. These limitations also provide avenues for future research in this domain.

One of the main limitations concerns the sampling strategy. Participants were selected using a non-probability criterion, which limits the statistical representativeness of the sample. Although participants had experience in digital transformation contexts and direct interaction with AI tools, the findings cannot be generalized to all organizations or HR professionals. Therefore, future studies should adopt probabilistic sampling methods that encompass different industry sectors, geographic regions, and levels of digital maturity.

Another limitation relates to the cross-sectional design of the quantitative study, which prevents the analysis of how perceptions evolve over time. Given that AI adoption is a dynamic process influenced by contextual factors, longitudinal studies could provide deeper insights into how perceptions of applicability, challenges, and barriers evolve across different stages of technological implementation.

The proposed model focuses on perceptions of applicability, challenges, and barriers, but does not consider other dimensions that may influence the intention to adopt AI – such as individual attitudes, leadership support, organizational culture, or market competitiveness. Future research could expand the model to include these variables and develop more comprehensive and explanatory theoretical frameworks. The self-reported nature of the data constitutes another limitation, as responses may have been influenced by social desirability or individual interpretations of the survey items.

It is also recommended that comparative studies be conducted among organizations with different levels of digital maturity, to identify distinct adoption patterns and tailored strategies for managing challenges and barriers.

Finally, future research should further explore the ethical and legal barriers qualitatively, since these did not show a significant impact in the quantitative model, yet remain widely cited in the literature.

Although this study helps address the research gap regarding AI adoption in HRM, numerous topics remain unexplored. These demand multidisciplinary approaches that are methodologically rigorous and sensitive to the complexity of technologies in the workplace context.

CONCLUSION

This study aimed to analyse how the perceived applicability of AI influences the intention to use it in HRM in the future. Based on a multiple moderation model, it also sought to understand whether the challenges and barriers to AI implementation condition this relationship. The results showed that the perceived applicability of AI has a direct and positive impact on the intention to adopt it in the future. Furthermore, perceived challenges were found to act as a significant moderator, intensifying the effect of applicability in more demanding contexts. This finding suggests that when difficulties are strategically addressed, they may reinforce the perceived value of AI as an innovation enabler.

On the other hand, structural barriers showed no significant effect, either as direct predictors or as moderators. The lack of impact may be related to the fact that professionals tend to prioritise the practical benefits of technology over the identified obstacles. These findings indicate that AI acceptance depends more on perceived usefulness and the way challenges are managed than on the existence of external limitations.

The adopted approach enables a broader understanding of AI adoption in HRM by considering contextual variables that are not always emphasised in existing studies. In summary, the successful adoption of AI in HRM requires not only effective technologies but also an organisational culture oriented towards innovation, employee development, and the strategic management of internal challenges.

REFERENCIAS

Abaas, G., & Robbins, S. (2024). *Artificial intelligence implementation in Human Resources: Ethical challenges and performance benefits* (published online). https://doi.org/10.13140/RG.2.2.20436.21125

Adabala, S. (2025). The Importance of data analytics in modern HR Practices. International Journal of Innovative Research and Creative Technology, 8(6), 1-16. https://doi.org/10.5281/zenodo.14613648

Ajunwa, I. (2025). An Auditing Imperative for Automated Hiring Systems. *Harvard Journal of Law & Technology, 34*(1), 1-45. http://dx.doi.org/10.2139/ssrn.3437631

Albassam, W. (2023). *The power of artificial intelligence in recruitment: An analytical review of current ai-based recruitment strategies*. *International Journal of Professional Business Review*, 8(6), 1-25. https://doi.org/10.26668/businessreview/2023.v8i6.2089

Al-Mamary, Y., Alshallaqi, M., & Al-Harbi, M. (2024). The impact of Artificial intelligence on Human Resource Management. Scientific African, 17, 1-6.

Almeida, M. (2023). *Risk-based Artificial Intelligence regulation and its responsiveness*. *Revista de Direito Setorial e Regulatório, 9*(1), 1-25.

An, H., Acquaye, C., Wang, C., Li, Z., & Rudinger, R. (2024). *Do large language models discriminate in hiring decisions on the basis of race, ethnicity, and gender?* (published online). https://doi.org/10.48550/arXiv.2406.1048

Bankar, S., & Shukla, K. (2023). Performance management and artificial intelligence: A futuristic conceptual framework. In S. Grima, K. Sood, & E. Özen (Ed.) Contemporary Studies of Risks in Emerging Technology (pp. 341-360). Emerald Publishing Limited. https://doi.org/10.1108/978-1-80455-566-820231019

Bardin, L. (2016). Content analysis. Edições 70.

Basnet, S. (2024). *The impact of AI-Driven predictive analytics on employee retention strategies*. *International Journal of Research and Review*, 11(9), 50-65. https://doi.org/10.52403/ijrr.20240906

Bersin, J. (2019). The impact of artificial intelligence on human resources management. Journal of Arts and Management, 3(2), 14-18.

Bujold, A., Roberge-Maltais, I., Parent-Rocheleau, X., Boasen, J., Sénécal, S., & Léger, P. (2024). Responsible artificial intelligence in human resources management: a review of the empirical literature. AI and Ethics, 4(4), 1185-1200. https://doi.org/10.1007/s43681-023-00325-1

Chakraborti, T., Isahagian, V., Khalaf, R., Khazaeni, Y., Muthusamy, V., Rizk, Y., & Unuvar, M. (2020). From robotic process automation to intelligent process automation: emerging trends (published online). https://doi.org/10.1007/978-3-030-58779-6_15

Chui, M., Manyika, J., & Miremadi, M. (2016). Where machines could replace humans-and where they can't (yet). The McKinsey Quarterly, 1-12.

Creswell, J., & Clark, V. (2018). Designing and conducting mixed methods research (3rd ed.). SAGE Publications.

Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340. https://doi.org/10.2307/249008

Du, J. (2024). Do humans trust AI in HRM? Why do? Why not?: Insights from a decade of research. Journal of Research in Social Science and Humanities, 3(7), 20-36. https://doi.org/10.56397/JRSSH.2024.07.04

El Garem, R. (2024). *Impact of AI on employee onboarding processes*. *Journal of Contemporary Employee Studies*, 15(4), 72-85. https://doi.org/10.21608/jces.2024.409688

European Commission (2019). Ethics guidelines for trustworthy AI. European Union.

Fenwick, A., Molnar, G., & Frangos, P. (2024). Revisiting the role of HR in the age of AI: bringing humans and machines closer together in the workplace. Frontiers in artificial intelligence, 6, 1-10. https://doi.org/10.3389/frai.2023.1272823

Ferrara, E. (2024). *Fairness and bias in Artificial Intelligence: A brief survey of sources, impacts, and mitigation strategies*. *Sci, 6*(1), 1-15. https://doi.org/10.3390/sci6010003

Gao, Y. & Liu, H. (2023). Artificial intelligence-enabled personalization in interactive marketing: a customer journey perspective. Journal of Research in Interactive Marketing, 17(5), 663-680. https://doi.org/10.1108/JRIM-01-2022-0023

Halid, H., Ravesangar, K., Mahadzir, S., & Halim, S. (2024). Artificial intelligence (AI) in human resource management (HRM). In Building the Future with Human Resource Management (pp. 37-70). Springer International Publishing.

Han, L. (2024). Challenges and opportunities for corporate human resource management in the context of artificial intelligence. International Journal of Global Economics and Management, 2(2), 147-152. https://doi.org/10.62051/ijgem.v2n2.20

Hayes, A. (2018). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. The Guilford Press.

Ijomah, T., Iyelolu, T., & Agu, E. (2024). AI-Driven decision support systems in management: enhancing strategic planning and execution. *International Journal on Recent and Innovation Trends in Computing and Communication*, *12*(1), 45-56.

Ionescu, A., Titov, S., & Izadi, M. (2025). A multi-agent onboarding assistant based on large language models, retrieval augmented generation, and chain-of-thought (published online). https://doi.org/10.48550/arXiv.2503.23421

Kekevi, U., & Aydin, A. (2022). Real-time big data processing and analytics: Concepts, technologies, and domains. Journal of Computer Science, 7(2), 111-123. https://doi.org/10.53070/bbd.1204112

Khan, F., Khan, N., & Aslam, A. (2024). *Adoption of Artificial Intelligence in Human Resource Management: An application of TOE-TAM Model. Research and Review: Human Resource and Labour Management*, 5(1), 22-36.

Khandelwal, K., Upadhyay, A., & Rukadikar, A. (2024). The synergy of human resource development (HRD) and artificial intelligence (AI) in today's workplace. Human Resource Development International, 27(4), 622-639. https://doi.org/10.1080/13678868.2024.2375935

Maharaj, A., & Obalade, G. (2025). *Artificial intelligence innovations in talent recruitment, retention, diversity mapping within South Africa: A meta-narrative analysis*. *Journal of Infrastructure, Policy and Development*, 9(2), 1-16. https://doi.org/10.24294/jipd10352

Mashudi, L., Fauziah, A., Windriya, N., & Kholidin (2025). The Role of AI-Driven HR Systems in Enhancing Employee Performance and Data Security in Modern Organizations. *Journal of Information Systems Engineering & Management, 10*(2), 520-535. https://doi.org/10.52783/jisem.v10i2.2448

Mirishli, S. (2025). *Ethical implications of AI in data collection: balancing innovation with privacy*. *Ancient Land, 6*(8), 40-55. https://doi.org/10.36719/2706-6185/38/40-55

Nyathani, R. (2023). AI in performance management: Redefining performance appraisals in the digital age. Journal of Artificial Intelligence & Cloud Computing, 2(4), 1-5.

Ong, X., & Lim, K. (2023). *SkillRec: A data-driven approach to job skill recommendation for career insights* (published online). https://doi.org/10.48550/arXiv.2302.09938

Oni, S. (2025). *Integrating AI into SME budget forecasting: Opportunities and challenges* (published online).

Palos-Sánchez, P., Baena-Luna, P., Badicu, A., & Infante-Moro, J. (2022). Artificial intelligence and human resources management: A bibliometric analysis. Applied Artificial Intelligence, 36(1), 1-29. https://doi.org/10.1080/08839514.2022.2145631

Pedrami, M., & Vaezi, S. (2025). Factors influencing artificial intelligence adoption in human resource management: a meta-synthesis and systematic review of multidimensional considerations. Journal of Organizational Management, 12(3), 45-67. https://doi.org/ 10.1108/JWAM-10-2024-0158

Prikshat, V., Malik, A., & Budhwar, P. (2023). *Employee involvement in AI-driven HR decision-making*. South African Journal of Human Resource Management, 21 (published online).

Qamar, Y., Agrawal, R., Samad, T., & Jabbour, C. (2021). When technology meets people: the interplay of artificial intelligence and human resource management. Journal of Enterprise Information Management, 34(5), 1339-1370. https://doi.org/ 10.1108/JEIM-11-2020-0436

Russell, S., & Norvig, P. (2020). Artificial intelligence: A modern approach (4th ed.). Pearson.

Sakka, F., El Maknouzi, M., & Sadok, H. (2022). Human resource management in the era of artificial intelligence: Future HR work practices, anticipated skill set, financial and legal implications. Academy of Strategic Management Journal, 21(S1), 1-14

Silva, R. (2024). The concepts of informational ergonomics applied to product design. Revista de Ergonomia e Design, 10(1), 30-45.

Simkute, E., Ajunwa, I., Binns, R., & Holstein, K. (2024). When AI systems are not adopted: an in-depth study of obstacles to adoption of AI systems by scientific experts (published online). https://doi.org/10.48550/arXiv.2403.16895

Sithambaram, R., & Tajudeen, F. (2023). Impact of artificial intelligence in human resource management: a qualitative study in the Malaysian context. *Asia Pacific Journal of Human Resources, 61*(4), 821-844. https://doi.org/10.1111/1744-7941.12356

Sundari, S., Silalahi, V., Wardani, F., Siahaan, R., Sacha, S., Krismayanti, Y., & Anjarsari, N. (2024). Artificial Intelligence (AI) and automation in Human Resources: Shifting the focus from routine tasks to strategic initiatives for improved employee engagement. East Asian Journal of Multidisciplinary Research, 3(10), 4983-4996. https://doi.org/10.55927/eajmr.v3i10.11758

Syaharani, D., & Yasa, N. (2022). *The Role of Trust as Mediation between Perceived Usefulness and Perceived Ease of Use on Repurchase Intention*. *International Journal of Social Science and Business*, *6*(2), 1-10. https://doi.org/10.23887/ijssb.v6i2.38522

Taslim, W., Rosnani, T., & Fauzan, R. (2025). Employee involvement in AI-driven HR decision-making: A systematic review. SA Journal of Human Resource Management, 23, 1-10.

Thilagavathy, R., & Venkatasamy, R. (2023). Artificial Intelligence and its role in shaping organizational work practices and culture. Administrative Sciences, 14(12), 316. https://www.mdpi.com/2076-3387/14/12/316

Triguero, I., Molina, D., Poyatos, J., Del Ser, J., & Herrera, F. (2023). General purpose Artificial Intelligence systems (GPAIS): Properties, definition, taxonomy, societal implications and responsible governance (published online). https://doi.org/10.48550/arXiv.2307.14283

Tursunbayeva, A., Pagliari, C., Di Lauro, S., & Antonelli, G. (2022). The ethics of people analytics: risks, opportunities and recommendations. Personnel Review, 51(3), 900-921. https://doi.org/10.1108/PR-12-2019-0680

Übellacker, T. (2025). Making sense of AI limitations: How individual perceptions shape organizational readiness for AI adoption (published online). https://doi.org/10.48550/arXiv.2502.15870

Venkatesh, V., & Davis, F. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management science, 46(2), 186-204. http://dx.doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M., Davis, G., & Davis, F. (2003). User acceptance of information technology: Toward a unified view. MIS quarterly, 27(3), 425-478. https://doi.org/10.2307/30036540

Vishwakarma, L., & Singh, R. (2023). An analysis of the challenges to human resource in implementing artificial intelligence. In The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part B (pp. 81-109). Emerald Publishing Limited. https://doi.org/10.1108/978-1-80455-662-720230006

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2023). Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review. Artificial intelligence and international HRM, 33(3),1-30https://doi.org/10.1080/09585192.2020.1871398

Wongras, P., & Tanantong, T. (2023). An extended UTAUT model for analyzing users' Acceptance factors for artificial Intelligence adoption in human resource recruitment: A case study of Thailand. Education and Information Technologies, 3(7), 13-27. https://doi.org/10.20944/preprints202311.1612.v1

Yanamala, K. (2023). Transparency, privacy, and accountability in AI-enhanced HR processes. Journal of Advanced Computing Systems, 3(3), 10-18. https://doi.org/10.69987/JACS.2023.30302

Yawar, M., & Hakimi, M. (2025). The Impact of Artificial Intelligence Technology on Human Resources Performance in Organizations. *Euro-Global Journal of Linguistics and Language Education*, *2*(1), 96-108. https://doi.org 10.69760/egjlle.2500013

Zhang, A., & Lee, M. (2025). *Knowledge workers' perspectives on AI training for responsible AI use* (published online). https://doi.org/10.48550/arXiv.2503.06002

