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AI MEETS HR – SYSTEMATIC REVIEW OF IMPLEMENTATION AND OPERATIONAL BARRIERS

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Purpose: This paper aims to explore the main barriers to the adoption and practical functioning of artificial intelligence in HRM. The goal is to provide a structured, multidimensional understanding of the challenges organizations face when implementing AI in HR processes.
Design/methodology/approach: The study is based on a systematic literature review of 24 peer-reviewed academic publications from 2020 to 2024. A thematic analysis was employed to identify and categorize barriers, drawing from empirical and conceptual research across different sectors and regions.
Findings: The review reveals a complex landscape of barriers spanning psychological, social, organizational, technological, and legal domains. These include lack of digital competencies among HR professionals, poor data quality, resistance to change, low trust in algorithmic systems, and ethical concerns. The findings highlight that AI implementation requires organizational and cultural transformation.
Research limitations/implications: The findings are limited by the scope and diversity of the selected literature, which is predominantly English-language and spans various contexts.
Practical implications: For successful AI adoption in HR, organizations must invest in digital and analytical skill development, ensure data quality, promote transparency and explainability in AI systems, and actively involve stakeholders in the implementation process.
Social implications: The integration of AI into HRM carries significant social implications, particularly regarding fairness, employee autonomy, and workplace relationships. Algorithmic bias may reinforce existing inequalities, while the automation of human-centric processes risks dehumanizing HR practices. Additionally, concerns about privacy, surveillance, and job insecurity can lead to resistance and technostress among employees.
Originality/value: This paper contributes a synthesized and structured analysis of current academic insights on AI-related challenges in HRM. It offers a foundation for evidence-based strategies, highlights research gaps, and encourages a systemic, human-centred approach to digital transformation in HR.
Keywords: Artificial intelligence, Human resource management, AI implementation, Barriers, Organizational transformation.
Category of the paper: Research paper.

1. Introduction

The modern economy is characterised by an increasing pace of technological change, which compels organisations to implement more advanced solutions, including those based on artificial intelligence (AI). Digital transformation also affects human resource management (HRM), introducing new challenges, technological expectations, and opportunities. Organisations making more intensive use of information technologies and data-driven capabilities are confronted with a key question: how can they effectively manage human resources, attract and develop talent, and make sound personnel decisions in an environment of uncertainty and rapid change?

The application of intelligent solutions in business is widespread in areas such as market analysis, product development, marketing, sales, customer service, and logistics. The introduction of AI can contribute to improved efficiency, greater decision-making precision, and increased customer and employee satisfaction. Therefore, it is no surprise that this technology has also gained attention in the HR context, where AI can support or, in some cases, even redefine the way personnel functions are carried out (Verma et al., 2023).

Despite growing interest in and the recognised potential of AI technologies, their implementation and everyday use in HR remains limited (Murugesan et al., 2023). This indicates several barriers and challenges that hinder the widespread adoption of these solutions. Although such obstacles often stay in the shadow of optimistic digital transformation visions, they appear to have a tangible impact on HR practice.

Identifying these barriers has thus become an important area of research, both from a scientific and a practical perspective. This gap in the literature allows for formulating a research problem focused on identifying the limitations and risks associated with the implementation and use of AI in HRM. To address this problem, the following research questions were posed:

RQ1: What factors limit the implementation of AI solutions in the HR domain?

RQ2: What factors most frequently hinder the everyday use of AI in HR activities?

Answering these questions will make it possible to identify key obstacles and understand their origins and characteristics knowledge that, in turn, can support the development of effective mitigation strategies. A deeper understanding of AI-related barriers in HR may serve as a foundation for a responsible and effective digital transformation of the HR function.

2. Artificial Intelligence in Human Resource Management

From a semantic perspective, artificial intelligence (AI) can be defined as a set of characteristics of intelligence or parts thereof attributed to an unnatural entity. According to the Merriam-Webster Dictionary (2023), AI is the capability of a machine to imitate intelligent human behaviour. One of the pioneers in the field, John McCarthy, defined AI as "the science and engineering of making intelligent machines, especially intelligent computer programs". In a project proposal from 1955, he stated that the goal of research was to create machines capable of using language, forming abstractions, and solving problems that had previously been reserved for humans (McCarthy et al., 1955).

AI can thus be understood as an attempt to replicate human cognitive processes in a machine not as a science-fiction concept but as a practical, interdisciplinary idea. Murphy (2012) describes AI as a technology that enables machines to perform tasks requiring human intelligence. Among the techniques used are machine learning, natural language processing, computer vision, and robotics. AI systems are those capable of learning from data and improving their performance over time, making decisions based on information and data and solving problems creatively and effectively.

AI algorithms are instructions that allow machines to self-improve based on input data. Key features of AI include adaptability, the ability to interpret context, natural interaction with humans, and, in some cases, autonomous decision-making.

The added value of AI stems from its ability to integrate data from various sources (e.g., ERP, CRM, social media, mobile devices) and analyse it to identify patterns and support decision-making, often at a level of complexity unattainable by humans.

The first references to AI use in HRM date back to 1994 and concerned expert systems. In subsequent years, developments included fuzzy logic (2000), neural networks (2001), data mining (2006), genetic algorithms (2008), and machine learning (2011) (Quamar et al., 2021). The dynamic growth of computing power and access to large datasets enabled the popularisation of generative solutions such as chatbots and virtual assistants. Although many of these technologies existed earlier, they have only recently become widely accessible commercially.

Due to the diversity of applications, providing a definitive definition of AI in HRM is difficult. It may refer to comprehensive human resource management systems and specialised applications automating a single process. The diversity of solutions and the degree of integration make comparing statistical data challenging.

AI technologies are present in nearly every area of HRM and at all levels of management: from strategic planning (Chakraborty et al., 2020; Gélinas et al., 2022; Verma et al., 2023) through recruitment and selection (Goncalves et al., 2022; Bhatt, 2023; Li et al., 2023), training and development (Faqihi, Miah, 2023; Murugesan et al., 2023), performance appraisal

(Böhmer, Schinnenburg, 2023), and compensation (Gélinas et al., 2022), to employee relations as well as legal and ethical issues. The literature emphasises that AI supports the entire employee life cycle, from attracting candidates to offboarding, integrating tasks, and increasing organisational efficiency (Chakraborty et al., 2020; Li et al., 2023).

When discussing the use of AI in HR, it is important to examine the type of work being performed. The literature highlights three main domains: automation of operational processes, data analysis, and support or automation of decision-making processes. AI systems can combine these functions, creating synergy from data processing and interpretation to taking action (Shaw et al., 2019). However, this approach does not imply full autonomy of systems; the dominant model remains one of human-machine collaboration, a role that continues to evolve. The emerging concept of hybrid HR emphasises the complementarity of human and technological functions.

In the operational domain, AI can automate various administrative and transactional tasks. For example, this technology is used in document creation and circulation (e.g., job postings, newsletters, contracts), meeting organisation and documentation, performance appraisal processes, document archiving, and HR and payroll services, including salary and benefits calculations. AI can also support communication between employees and the HR department, for instance, through chatbots that handle employee inquiries, complaints, and requests (Korzyński et al., 2023).

In data analysis, AI enables the processing large volumes of information from internal (HRIS systems, operational data) and external sources (labour market data, benchmarks). This facilitates more accurate candidate evaluations not only in terms of competence but also cultural fit. AI also supports training needs analysis, talent identification, career path planning, and the prediction of workplace risks. By analysing data from sensors, cameras, and other sources, these systems can contribute to occupational health and safety efforts (Murugesan et al., 2023).

AI is particularly significant in People Analytics and Compensation & Benefits. In the first case, AI allows for predicting employee behaviour (e.g., absenteeism, turnover) and measuring productivity for instance, by analysing work time and task completion. This enables continuous process adjustments and the identification of areas for improvement. In compensation, AI systems can analyse the alignment of pay policies with market benchmarks, forecast the impact of benefits on employee performance, and support accurate salary calculations, reducing the risk of errors (Murugesan et al., 2023).

The use of AI in decision-making processes is primarily associated with the potential to reduce subjectivity and improve decision accuracy. Algorithms can assist in matching candidates to positions, recommending bonuses, or making HR decisions based on performance data. Such approaches support rational workforce management and cost-effectiveness (Kshetri, 2021).

The integration of AI technologies into HRM, however, goes beyond automation. AI can act as an integrator of HR functions, connecting data, processes, and decisions into a cohesive whole. These systems can deliver personalised HR services in real-time, from training recommendations and career development suggestions to modelling flexible working conditions. Such solutions improve employee experience, enhancing engagement, retention, and performance (Kshetri, 2021). These capabilities are key drivers of interest in AI technologies in HR as tools for efficiency and as transformative elements in managing the HR function.

3. Research Methodology

From A systematic literature review was conducted to address the research questions posed in this study, allowing for a rigorous and structured analysis of the existing scientific body of knowledge in the relevant domain (Czakon, 2015). This review followed an established research procedure, emphasising transparency in the selection process, clearly defined inclusion criteria, and thematic content analysis.

The analysis focused on academic publications exploring barriers and risks associated with the implementation and use of artificial intelligence in human resource management (HRM). The empirical material was sourced from full-text databases Scopus and Web of Science (WoS), which are considered the most comprehensive repositories indexing peer-reviewed management literature (Mongeon, Paul-Hus, 2016). The choice of these databases was motivated by their thematic coverage and the possibility of integrating bibliographic data from various types of publications (articles, book chapters, conference proceedings) into a unified analytical format.

In both databases, an identical search query string was applied. It included four key components: references to artificial intelligence, HRM functions, the application phase, and potential limitations. The full query was as follows: (“AI” OR “Artificial Intelligence”) AND (“HR” OR “HRM” OR “Human Resources” OR “Human Resources Management” OR “People Management” OR “Personnel Management”) AND (“implementation” OR “adoption” OR “application” OR “launch” OR “usage” OR “utilisation”) AND (“limitation” OR “problems” OR “difficulties” OR “barriers”).

The search results were refined by applying additional selection criteria in the next stage of the database development process. Only publications published between 2020 and 2024, written in English and classified as peer-reviewed journal articles, were included. To further increase the relevance of the selected materials, thematic filtering was applied based on the subject classifications of each database. For the Scopus database, the category “Business, Management & Accounting” was selected, while in Web of Science (WoS), the filters “Business” and

"Management" were applied. After implementing these initial filters, 60 results were retrieved from Scopus and 39 from Web of Science. Duplicate records were identified and removed, reducing the dataset by 26 entries. The remaining publications were screened through abstract analysis to assess their alignment with the research focus of this review. At this stage, 40 articles were excluded due to thematic mismatch.

The selection process also involved exclusion criteria to eliminate studies that did not meet the thematic assumptions of this review. The following types of publications were excluded:

- Articles focused on technologies without explicit reference to artificial intelligence.
- Publications discussing specific AI technologies without reference to their use in HR.
- Studies examining AI in HR without reference to barriers, limitations, or challenges.

Ultimately, 33 academic articles were qualified for full-text analysis, of which 24 were selected for final inclusion after in-depth verification based on their conceptual, methodological, and thematic alignment with the scope of this review (Table 1).

Table 1.
Searching strategy

Procedure phase	Description
Phrase Search	N = 932
First-Level Inclusion Criteria	Publication year: All years from 2020 to 2024 Document type: Article Language: English N = 321
Second-Level Inclusion Criteria	Scopus subject area: Business, Management & Accounting, Web of Science Categories: Business, Management, N = 80
Duplicate Documents	Files cleaning (after all duplicate records are removed) N = 68
Abstract analysis	After files removed, N = 31
Full-text analysis	Final sample selected for further analysis: N = 24

Source: Own study.

A large number of excluded publications resulted from the previously mentioned ambiguity surrounding the definition of artificial intelligence and the growing popularity of the topic itself, which has led to frequent overuse of AI-related terminology. For example, some articles referenced AI only marginally, most often in the abstract, as a potential direction for future development, without any substantial discussion of implementation or actual use of AI in HR.

Among the 24 selected publications, three were published in 2020, one in 2021, two in 2022, six in 2023, and twelve in 2024. The increase in the number of publications appears to reflect the growing interest in and development of AI-based technologies, suggesting a further expansion of research in this field, thus reinforcing the relevance of the present study.

The full-text analysis revealed that 23 of the 24 articles identified barriers related to the implementation of AI in HR, and 15 linked to the practical use of already implemented systems. Most of the reviewed studies were empirical (16), including one experimental study and one case study, while the rest employed qualitative or quantitative methods (e.g., surveys and interviews). The remaining eight publications were theoretical or literature-based reviews.

The qualitative analysis of the material involved manual extraction of elements identified by the authors as barriers, difficulties, or limitations associated with AI implementation or use in HR-related contexts. Unique items were identified, and descriptions were assigned in a manner consistent with the reviewed sources. The preliminary analysis revealed significant variation in terminology, levels of detail, and conceptual scope, which prompted the researchers to adopt thematic analysis to organize and synthesize the data.

Thematic analysis, following the approach of Clarke and Braun (2016), facilitates the identification of patterns across qualitative data, integrating diverse sources and perspectives, both empirical and theoretical. In the initial phase, short, precise codes were generated to describe individual data units. These codes were then grouped into potential themes, which were subsequently organized hierarchically according to the method proposed by Attride-Stirling (2001), allowing for identifying key problem areas. In the pre-implementation phase, the main obstacles included social barriers, organizational and managerial barriers, as well as technological barriers. In the post-implementation phase, the barriers identified were primarily of a social nature, along with operational and functional barriers that emerged during the actual use of AI systems. In the process's final phase, the assigned themes' consistency and validity were reviewed, and the names and definitions were refined. The outcome was a consolidated catalogue of 21 barriers and limitations, ensuring internal coherence across the research procedure.

4. Discussion of Findings

4.1. Barriers and Limitations in the Implementation Phase of AI Solutions in HR Domains

A necessary condition for an organization to even consider implementing AI technologies in HR is an economic assessment, which typically considers factors such as costs, time, expected performance, customer satisfaction, decision-making accuracy, predictive capabilities, and the technological feasibility of implementation given the available resources (Cubric, 2020). Among the reviewed literature, only a few authors explicitly emphasize the economic dimension, and even then, it is usually presented as part of the pre-implementation analysis or as a motivating factor for managers. However, researchers tend to shift their focus from economic considerations to managerial attitudes during the actual implementation phase of AI technologies, which become the primary subject of investigation. For this reason, financial factors were not further explored in the subsequent stages of the discussion.

Table 2.
AI Implementation Barriers in HR

Category	Barrier	Source
Social Barriers	Fear of job loss (job insecurity)	(Qamar et al., 2021; Li et al., 2023; Rukadikar, Khandelwal, 2024)
	Resistance to change	(Qamar et al., 2021; Li et al., 2023; Rukadikar, Khandelwal, 2024; Suseno et al., 2022; Bazrkar, 2024)
	Low level of trust in AI / concerns about control	(Qamar et al., 2021; Rukadikar, Khandelwal, 2024; Cubric, 2020; Angelova et al., 2023; Islam et al., 2023; Paramita, 2024; Dutta, Mishra, 2023; Malin et al., 2023)
	Ethical concerns (discrimination, lack of transparency, privacy)	(Qamar et al., 2021; Li et al., 2023; Rukadikar, Khandelwal, 2024; Marler, 2024; Gélinas et al., 2022; Kshetri, 2021)
	Perceived threat to human decision-making autonomy	(Qamar et al., 2021; Angelova et al., 2023; Dutta, Poyil, 2023)
	Technostress / AI anxiety	(Rukadikar, Khandelwal, 2024; Suseno et al., 2022; Destriani et al., 2024)
Managerial and organisational Barriers	Lack of technological competencies (among managers/employees)	(Li et al., 2023; Rukadikar, Khandelwal, 2024; Suseno et al., 2022; Böhmer, Schinnenburg, 2023; Destriani et al., 2024; Cao, Nguyen, 2024; Bazrkar, 2024; Verma et al., 2023; Oswald et al., 2020)
	Absence of a clear strategy or vision for AI implementation in HR	(Böhmer, Schinnenburg, 2023; Angelova et al., 2023; Cao, Nguyen, 2024; Bhatt, 2023; Verma et al., 2023)
	Lack of managerial engagement and decision-making support	(Bhatt, 2023)
	Concerns about the diminishing role of HR ("dehumanisation of HR")	(Paramita, 2024; Dutta, Poyil, 2023)
Technological Barriers	Lack of AI system transparency ("black-box problem")	(Rukadikar, Khandelwal, 2024; Islam et al., 2023; Marler, 2024; Gélinas et al., 2022; Malin et al., 2023)
	Poor data quality/lack of training data	(Cubric, 2020; Destriani et al., 2024; Gélinas et al., 2022; Kshetri, 2021)
	High implementation costs vs. low return on investment (ROI)	(Yadav, Kapoor, 2024; Kshetri, 2021)
	Incompatibility with existing IT systems	(Cubric, 2020; Destriani et al., 2024; Yadav, Kapoor, 2024; Yue, 2023)

Source: Own study.

The analysis of sources confirms that implementing artificial intelligence (AI)-based systems in human resource management (HRM) encounters numerous limitations. These limitations emerge as early as the planning and decision-making phases of implementation. The barriers are complex, encompassing social, organisational, and technological factors (Table 2). Their interdependencies reinforce each other and reduce an organisation's readiness for digital transformation.

Among the social barriers, one of the key obstacles to AI implementation in HR is the fact that "Employees may be afraid of being replaced by AI" (Li et al., 2023), along with concerns about transferring many operations outside the HR function (Dutta, Poyil, 2023). It is suggested that automation of tasks previously performed by humans may lead to simplifying responsibilities and a diminished sense of professional agency and value. "Fear that smart machines have started to replace humans in the workplace is another barrier to AI implementation" (Suseno et al., 2022). Such fears are intensified when employees lack the necessary technological and analytical competencies. This leads to technostress, a loss of control, and fears that "AI will remove their autonomy" (Suseno et al., 2022). These concerns contribute to negative attitudes and a lack of trust in AI among employees and customers. "A lack of trust would reduce participants' emotive involvement, which is how they interpret the AI offering" (Dutta, Poyil, 2023). This challenge is related to technostress, chronic stress triggered by the need to adapt to changing tools and methods, lack of control, and efficiency pressure (Destriani et al., 2024). Paradoxically, technologies intended to support employee development generate new competency requirements, forcing constant knowledge updates and redefining professional roles. As a result, cognitive overload, reduced job satisfaction, and work-life imbalance are common.

In addition to psychological factors, organisational barriers are also significant. These include a lack of technological competencies among both managers and employees, the absence of strategy or vision for AI implementation, insufficient top management support, and concerns about the diminishing role of HR in the organisation.

Numerous authors emphasise that a lack of technological and analytical skills among HR professionals is a critical weakness of the field (Li et al., 2023; Rukadikar, Khandelwal, 2024; Suseno et al., 2022; Böhmer, Schinnenburg, 2023; Destriani et al., 2024; Cao, Nguyen, 2024; Bazrkar, 2024; Verma et al., 2023; Oswald et al., 2020). As Li et al. (2023) notes, "Lack of technological and digital skills may lead them to refuse to use AI." This competency gap also affects management, which often lacks a clear understanding of AI systems' capabilities and limitations. According to Suseno et al. (2022), "HR professionals need support and encouragement from leadership to fully integrate AI". A. Islam et al. (2023) further confirm this by stating that "Top management support emerges as the most significant factor in the adoption of AI technology in organisations". A lack of expertise is a barrier and a root cause of other social and technological limitations. Literature highlights that managerial attitudes, including openness to change, levels of anxiety, and expectations are just as critical as technical challenges (Cubric, 2020; Bhatt, 2023).

The final organizational barrier is the absence of a clear strategy or roadmap for AI adoption. As Yaday and Kapoor (2024) emphasize, "AI initiative strategy should also be launched by top management. There is evidence that regulations are effective in promoting AI technology". Managers who have experienced the benefits of intelligent systems are more likely to recognize the value of aligning AI with their HR strategies (Cao, Nguyen, 2024).

While the barriers mentioned above are primarily social and organizational, others are directly linked to the technological architecture and the nature of the data used. Foremost among these is the "black-box problem". which refers to the lack of transparency in AI system operations. This creates distance and distrust among employees who perceive algorithmic decision-making as opaque and difficult to understand (Rukadikar, Khandelwal, 2024; Islam et al., 2023; Marler, 2024; Gélinas et al., 2022; Malin et al., 2023). Technological solutions like machine learning are inherently complex, "limiting people's technological understanding, leading to critical information asymmetries" (Qamar et al., 2021). As Marler (2024) points out, "It is not enough to say the AI algorithm produced the answer". A lack of understanding of how AI reaches its conclusions can lead to justifiable concerns (Malin et al., 2023).

Another major limitation in implementing AI solutions is the lack of data, poor data quality, fragmentation, and difficulty in system integration (Cubric, 2020; Destriani et al., 2024; Gélinas et al., 2022; Kshetri, 2021). The data problem is directly tied to technological competencies. High-value data results from the engagement of competent and informed staff in HR departments and across all organizational units contributing to AI systems. A shortage of qualified professionals among HR specialists and managers is a core cause of data deficits. These competencies encompass data collection and processing and an awareness of organizational data culture. Researchers argue that the development of HR analytics is limited by a short-term approach to data management, challenges in maintaining data quality, and gaps in analytical skills (Conte, Siano, 2023). HRM processes rely on data from HRIS (Human Resource Information Systems) and other departmental systems. This makes data coordination and integration across disparate, inconsistent, and often unstructured sources a significant challenge especially when data are stored in different formats and languages and are not covered by formal audit procedures (Oswald et al., 2020). Given the magnitude of technical and organizational factors, maintaining data quality often becomes unmanageable for standard HR departments. Data quality is crucial because modern AI systems, especially those based on machine learning, require large datasets to produce reliable recommendations. Data scarcity, incompleteness, and poor-quality lead to flawed models and inaccurate outputs (Dutta, Mishra, 2023), potentially resulting in serious consequences for organizational decision-making. AI algorithms themselves are not immune to bias. Historical data shape decisions made by AI. If those data are unfair or biased, algorithms may reproduce and reinforce existing prejudices or discriminatory patterns embedded in the original datasets (Gélinas et al., 2022).

All the above factors pose significant limitations to implementing AI in HRM, which was the focus of the study's first research question.

4.2. Barriers and Limitations Related to the Functioning of AI in HR Domains

Organisations often encounter new challenges after implementing artificial intelligence systems in human resource management. These barriers emerge during the daily use of AI and are socio-psychological and operational-functional (Table 3).

Table 3.
Operational Barriers to AI in HR

Category	Barrier	Source
Social Barriers	Perceived unfairness of AI-driven decisions (e.g., in recruitment)	(Rukadikar, Khandelwal, 2024; Paramita, 2024; Gélinas et al., 2022; Malin et al., 2023)
	Dehumanisation of HR interactions	(Rukadikar, Khandelwal, 2024; Paramita, 2024; Dutta, Mishra, 2023)
	Lack of trust in AI system outputs	(Cubric, 2020; Rukadikar, Khandelwal, 2024; Suseno et al., 2022; Dutta, Mishra, 2023; Malin et al., 2023)

Cont. table 3.

Managerial and organizational Barriers	Difficulty in interpreting AI results by HR professionals	(Böhmer, Schinnenburg, 2023; Oswald et al., 2020; Malin et al., 2023)
	Overreliance on technology/loss of HR team autonomy	(Li et al., 2023; Paramita, 2024; Dutta, Poyil, 2023; Malin et al., 2023)
	Challenges with updating, adapting, and scaling AI systems	(Destriani et al., 2024; Gélinas et al., 2022; Verma et al., 2023)
	Inability to adjust algorithms to the organisational context	(Yadav, Kapoor, 2024; Bhatt, 2023; Verma et al., 2023)

Source: Own study.

The use of intelligent technologies in HR is associated not only with the challenges of implementation but also with their everyday use. The literature identifies two main categories of such barriers: social (social and relational) and managerial (organizational). Among the most frequently mentioned social factors is the lack of trust in the results and decisions generated by AI. HR employees and managers often question the reliability and neutrality of AI systems, which limits their full utilization (Malin et al., 2023). Serious concerns also arise from processing personal data collected from multiple sources, such as computer logs, sensors, messaging platforms, or monitoring systems, which can evoke associations with excessive surveillance and privacy violations. As a result, employees with strong positions in the labor market may leave the company if they feel overly monitored in their performance (Böhmer, Schinnenburg, 2023). The broad scope of data analyzed by AI systems may lead to suspicions of surveillance, especially when there is a lack of transparency in data usage and storage. In this context, "Trust and communication are key to effective AI engagement in HR" (Dutta, Mishra, 2023). The lack of trust is often linked to the perception that AI-generated outcomes are unfair, impersonal, and difficult to challenge. This is particularly relevant in recruitment, candidate selection, and performance appraisal processes, where users highlight the absence of social context and the excessive standardization of algorithms as potential sources of unequal treatment. "Biased algorithms can support inequality and discrimination […] transparency is essential to retaining applicants' confidence" (Rukadikar, Khandelwal, 2024). Gélinas et al. (2022) point to the issue of systemic biases embedded in algorithmic decision-making. This is connected to the problem of algorithmic discrimination, which may result in bias against employees based on gender, age, ethnicity, or other sensitive attributes (Kshetri, 2021). If historical data reflect patterns of nepotism, prejudice, or informal decision-making, algorithms may unintentionally perpetuate and reinforce them, creating a paradox in which a system designed to reduce human error replicates it (Kshetri, 2021; Paramita et al., 2024).

Another issue with implementing AI is the dehumanization of HR relationships and processes. Automating interactions through chatbots, assessment systems, or digital recommendations reduces opportunities for empathetic dialogue and personalized employee engagement. "Lack of human-to-human interaction in AI-driven processes can lead to impersonal connection and low trust" (Paramita et al., 2024). Digital isolation in employee development may also lead to reduced creativity and innovation.

One of the most frequently identified managerial challenges is interpreting AI-generated outputs, particularly when the algorithm's accuracy is perceived as flawed (Dietvorst et al., 2018; Prahl, Van Swol, 2017). This highlights the need to develop algorithmic literacy that fosters a reciprocal relationship between employees and algorithms, including human-assisted and machine-assisted roles (Paramita, 2024). Böhmer (2023) emphasizes that AI systems rely on complex mathematical models whose inner workings remain opaque to most users. Self-learning algorithms function as a "black box," with their reasoning processes difficult to understand even for specialists (Böhmer, Schinnenburg, 2023). As a result, organizations must invest in digital skills and user education, which poses an additional burden for HR departments. This issue is closely tied to data quality. Low-quality data with incomplete, outdated, or non-representative inputs can lead to incorrect conclusions and recommendations. Algorithms trained on such data may replicate systemic errors rather than eliminate them, posing a significant threat to the objectivity of HR processes. Functional limitations are also related to the inflexibility of AI systems, which rely on historical data and often fail to account for contextual, cultural, or individual variations.

Another post-implementation barrier in HR practice is the gradual transfer of responsibility to AI systems, simplifying and automating many employee tasks (Dutta, Poyil, 2023). This may result in the erosion of critical thinking and the neglect of intuition and experience in decision-making. Ardichvilli (2022) warns that the increasing delegation of tasks to AI may also limit employees' opportunities to develop competencies, share knowledge, and engage in intellectually meaningful work. "Automation of processes that leads to machines taking over tasks previously reserved for humans may contribute to job loss or reduction in job complexity" (Ardichvilli, 2022). As Chowdhury et al. (2023) note, managers supported by AI systems are more likely to make questionable decisions by shifting part of the responsibility to the technology.

At the systemic level, challenges such as scaling and adapting AI systems to different organizational sizes remain significant (Gélinas et al., 2022). As Malin et al. (2023) observe, "Maintenance costs are a disadvantage" because "Somebody has to take care of this technological achievement and provide content continuously." Feeding AI systems with new knowledge must align with evolving user expectations (Malin et al., 2023), and difficulties in this regard reduce algorithmic usefulness (Yadav, Kapoor, 2024), further fueling concerns about fairness and the lack of flexibility in AI systems tailored to generic use cases (Bhatt, 2023). Managerial and organizational barriers are both technical and competency related. Addressing them requires developing analytical skills, system-level AI management, and cultivating a data-driven learning culture.

The above analysis answers the second research question: What factors most frequently hinder the everyday use of AI in HR activities?

5. Conclusions and Recommendations

The following conclusions, recommendations, and research directions can be formulated considering the literature review. The analysis of publications concerning the implementation and use of artificial intelligence (AI) in human resource management (HRM) reveals a wide range of barriers from social to organizational and technological (Figure 1).

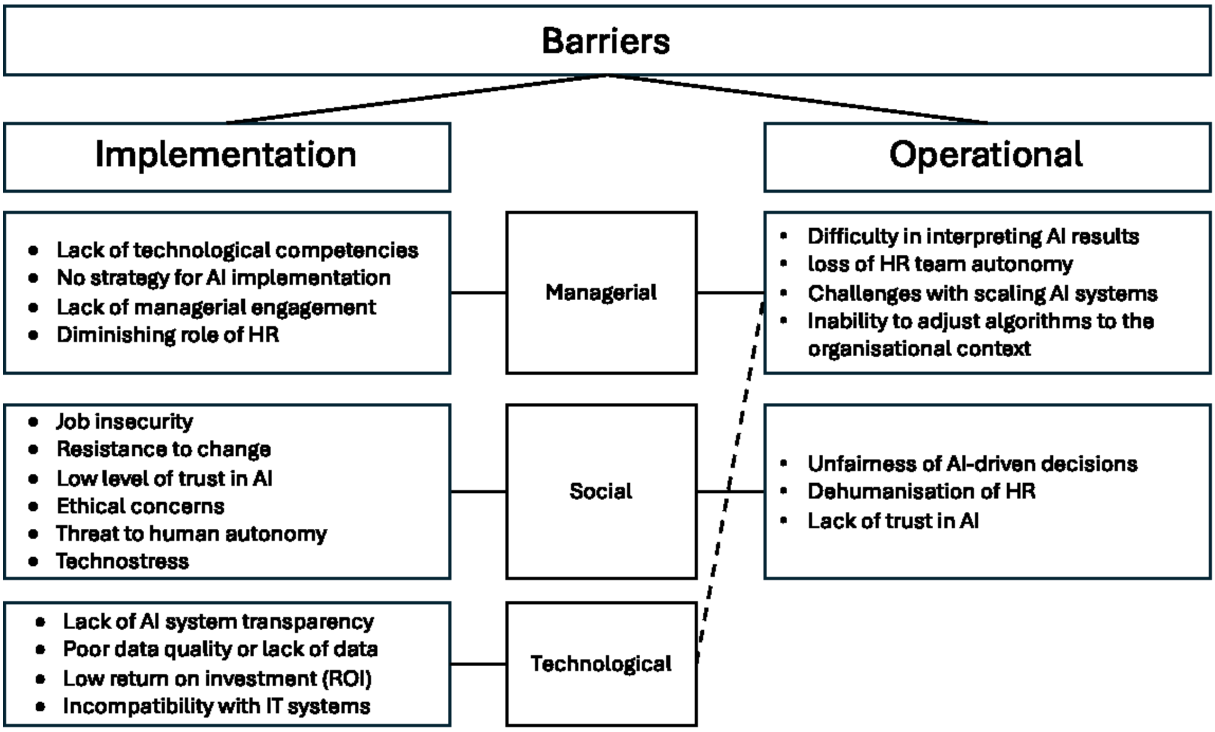

Figure 1. Classification of Implementation and Use Barriers of AI in HRM.

Source: Own study.

These barriers occur during the planning and implementation stages and during the day-to-day use of AI applications, indicating the complex and dynamic nature of digital transformation processes in HRM. Key obstacles include a lack of technological and analytical competencies, poor data quality, employee resistance to change, and low trust in algorithmic decision-making. Therefore, the integration of AI into HR practices requires not only technical adaptation but also a fundamental shift in organizational culture and in the way people management is conceptualized.

These findings also have important implications when viewed through the lens of strategic HRM frameworks. For instance, several of the identified barriers—such as lack of managerial engagement or an unclear strategic vision—directly hinder the HR function's ability to act as a Strategic Partner or Change Agent, as described in Ulrich's model. Similarly, operational challenges such as overreliance on AI systems or limited interpretability of algorithmic outputs may undermine the credibility of HR and its role as an advocate for employees. Integrating AI into HRM, therefore, should not be regarded solely as a technical upgrade but as a strategic transformation aligned with the core values and roles of the HR function.

Given these considerations, it is essential to formulate practical recommendations to support organizations in effectively integrating AI into HRM. First, it is necessary to develop digital and analytical competencies among HR professionals and managers. Previous research indicates that limited technological literacy and a lack of algorithmic thinking are among the primary sources of resistance and misinterpretation of AI-driven systems. Equally important is building trust in AI technologies, which can be achieved through the use of transparent and explainable models that allow users to understand how algorithms function and on what basis they generate recommendations. Another critical area is data governance. Organizations must establish clear standards for data collection, integration, and quality assurance, including the development of coherent information systems and appropriate control mechanisms. Ethical standards and privacy protection are also fundamental, particularly in relation to sensitive employee data. This requires compliance with legal regulations and transparent communication about the purpose and methods of data processing. Finally, the active involvement of stakeholders in the implementation process is vital. Engaging HR professionals, managers, and employees in the design and evaluation of AI applications fosters acceptance, reduces uncertainty, and reinforces a sense of shared responsibility for the success of digital transformation initiatives. Collectively, these actions create the foundation for the responsible and effective use of AI in managing human capital.

From the perspective of advancing the field of HRM, there is a clear need for more in-depth research on the impact of AI on the HR function, both theoretically and empirically. Current literature lacks well-developed conceptual frameworks for understanding how AI integration transforms job roles, the professional identity of HR practitioners, and interpersonal dynamics within organizations. Interdisciplinary research that bridges technological perspectives with insights from the social sciences is needed to capture the systemic nature of these transformations. Empirical studies—both qualitative and quantitative—should also be conducted to examine specific cases of AI implementation, its organizational outcomes, and employee responses. Case studies and longitudinal research are particularly valuable for identifying measurable effects and long-term consequences of AI adoption in HRM. This research agenda should further include exploration of the social and ethical implications of AI use in HR, including algorithmic bias, the marginalization of certain employee groups, and the opacity of decision-making processes. These concerns underscore the need for robust theoretical and practical frameworks to assess fairness, accountability, and transparency in AI applications. Future studies should also address sectoral and cultural comparisons, as there is limited knowledge about how barriers and enablers vary between public and private sectors or across geographic contexts such as Europe, Asia, and developing countries. Another important area for exploration is the long-term impact of AI on the HR function itself—specifically, the evolution of organizational processes and the emergence of new competency expectations for HR professionals. It is also essential to assess the effectiveness of managerial interventions, including training programs, communication strategies, and structural adjustments, in enhancing organizational readiness for AI adoption. Finally, given the expanding role of AI in HR decision-making, the academic community should contribute actively to the development of consistent ethical and regulatory standards governing AI use in HRM. Addressing these research directions can significantly support the sustainable, informed, and responsible development of HRM practices in the age of AI.

This article is based on a selected set of empirical and theoretical studies published between 2020 and 2024. The study's limitations primarily concern potential selection bias, including the predominance of English-language literature and the heterogeneity of the analyzed materials, which include case studies, quantitative research, and conceptual papers. Additionally, the diversity of research contexts—encompassing various geographic, sectoral, and organizational settings—may affect the comparability of findings. Furthermore, the literature reveals significant gaps, particularly the underrepresentation of research from developing countries and underexplored areas such as public administration and nonprofit organizations. As such, the findings presented herein should be interpreted as a synthetic overview of the current state of knowledge, identifying key trends and challenges rather than providing an exhaustive or definitive account of the topic.

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