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UNDERSTANDING HOW AI-DRIVEN INNOVATIONS RESHAPE HUMAN RESOURCE MANAGEMENT AND INFLUENCE ORGANIZATIONAL EFFECTIVENESS

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ABSTRACT

Objective: This research aims to understand the use of Artificial Intelligence (AI) in human resource management (HRM), identify the challenges of its integration, and explore its impact on operational efficiency, decision-making, and employee work experience.

Research Design & Methods: This study used a qualitative approach, conducting in-depth interviews and analyzing relevant literature. The data was thematically analyzed to explore employees' perceptions, hopes, and fears and the organization's strategy for adopting AI in HR.

Findings: Findings show that AI has great potential in improving the effectiveness of HR management, especially in terms of process efficiency, decision-making accuracy, and personalization of employee experience. However, barriers such as a lack of digital competency, reliance on conventional HR practices, and concerns about losing the human dimension remain crucial. Employees show mixed responses, ranging from enthusiasm for efficiency to anxiety about job security and dehumanizing work processes.

Implications & Recommendations: This research recommends strengthening digital literacy and adaptive training for HR practitioners, developing ethical and human-centered AI integration policies, and ensuring organizations maintain a balance between technological efficiency and human touch in managerial practices.

Contribution & Value Added: This research contributes to the conceptual and practical understanding of AI integration in HR management. Its added value is the presentation of a multidimensional perspective on addressing digital transformation in the HR domain, both from the organization and employee sides.

Keywords: Digital Transformation, Operational Efficiency, Technology Adaptation.

JEL codes: M15, D23, J24.
Article type: research paper

INTRODUCTION

Human Resource Management (HRM) has metamorphosed substantially over the past decade. Initially, it was seen as an administrative task, but now HRM has evolved to include strategic decision-making and the implementation of technological advancements, especially in terms of artificial intelligence (AI) (Rodgers et al., 2023). Historically, human resource management (HRM) has concentrated on managing fundamental aspects related to employees, maintaining employee records, and ensuring compliance with applicable regulations (Hassell et al., 2016). However, with globalization and the increasing complexity of business operations in the late 20th century, there was a shift in thinking regarding human potential management. Companies began to understand that the workforce is an important asset in providing a competitive advantage and started investing in potential management, leadership improvement, and corporate culture (Zhang & Chen, 2024).

The significance of human capital parsing grew in the 2000s when data-driven decisions began to influence hiring processes, performance management, and strategies for retaining employees (Polyakova et al., 2020).

As HRM evolved, other changes also took place simultaneously, leading to the development of Artificial Intelligence technology. Initially, this technology only existed in fields such as finance and manufacturing, but it began to touch various other sectors, including entertainment, healthcare, and education, in the 2010s (Javaid et al., 2022). Incorporating artificial intelligence technology in human resource management practices is a breakthrough. The automated screening of job applications with natural language methods allows selection procedures to be conducted appropriately and fairly. With proper review facilitated by AI algorithms, we can now predict the likelihood of labor efficiency, which results in companies competently retaining talented employees (Bobitan et al., 2024). Then, using chatbots and AI (Artificial Intelligence) helps the question and answer process with workers in real time, thus establishing better communication between the Human Resources division and workers (Majumder & Mondal, 2021). However, the collaboration of human resource management and artificial intelligence has problems. Ethical issues exist as AI makes important judgments, resulting in a person's existence. There is an ongoing debate about the need for open processes in AI algorithms and the possibility of unintended subjectivity in mechanized mechanisms (Koulu, 2020).

AI refers to a broad category of technologies that enable computers to perform tasks requiring human thinking skills, including making flexible decisions under all conditions (Tambe et al., 2019). In academic research, there is a complex debate about the different types of digital tools and methods in AI and their potential impact on firms' profitability from existing business solutions (Aouadni & Rebai, 2017; Castellacci & Bardolet, 2019). In this context, the recent push for academic research on AI in human resource management has attracted significant attention in key journals in human resource management, along with related disciplines such as international management, information technology, and general management. Therefore, studies on the interaction between AI and HRM are increasingly interdisciplinary (Gong et al., 2025). References to AI and HRM are still limited to how AI and similar technologies can provide practical solutions for HRM and subfunctional areas and how AI-supported HRM functions relate to other operational tasks to achieve greater results for their organizations.

Although the understanding of AI-HRM is minimal, much information states that recent advances in automation technology provide significant benefits to human resource management. Moreover, both local and multinational enterprises (MNEs) have realized the benefits of using AI-based tools and methods to improve employee satisfaction, commitment, and engagement at work (Castellacci & Bardolet, 2019), productivity (Wirtz et al., 2019), employee performance, and cost efficiency in HRM (Azadeh & Zarrin, 2016); retain employees, and make more effective decisions (Azadeh & Zarrin, 2016), while reducing HR-related operational costs and other expenses. There is a significant increase in interest in exploring AI and its impact on specific aspects of human resource management (Budhwar et al., 2023). There is a growing interest in exploring artificial intelligence and its impact on subfunctional areas of HRM. For example, researchers argue that emerging AI-based HRM technologies can assist in talent acquisition, development, evaluation, and retention in large multinational technology companies. It can also support processes ranging from recruitment to selection, assessment, and interviewing of the most suitable candidates, including advertising for Industry 4.0 to attract new job profiles and evaluate the effectiveness of employee training (Chérif et al., 2021). This aspect has implications for IHRM as contextual influences such as language differences, culture, and cross-border institutions require diverse databases for the application of AI, thereby reducing biases that may exist in limited data and single-country contexts. Although references to AI-powered HRM show positive results, other opinions propose the need to investigate the negative impact of this advanced technology on organizations and employees. Ignoring adverse factors can lead to unintended consequences, such as high employee turnover, reduced job satisfaction, loss of customer satisfaction, high costs, and ultimately affect business performance and the organization's overall reputation. In addition, experts point out that there are limitations that often arise when applying AI in human resource management, as a result of the complexity of HR phenomena, lack of sufficient data, accountability questions related to fairness, and other ethical and legal issues, as well as the possibility of adverse reactions from employees to management decisions made through algorithms based on data (Tambe et al., 2019).

This research aims to increase understanding of the reach of AI (Artificial Intelligence) in HRM, examining the various uses of HRM that are currently affected or likely to be affected by AI developments. Secondly, this research also aims to recognize the various obstacles that arise due to the introduction of AI to traditional Human Resource Management, including problems about workers' work ethic, the mismatch of employee qualifications, and work ethics in the company. Thirdly, this research helps read and explore the opportunities in using AI regarding analysis and prediction in Human Resources, personalized employee work experience, tapping into employee potential, and employee efficiency. Fourth, this research also aims to provide recommendations based on the obstacles and opportunities identified by the system, provide strategic advice to organizations for effective integration of AI in Human Resource Management, and provide a balance between technology and innovation in a centralized or human-centered method (workers). With the purpose of this study, the authors intend to provide knowledge and advice that will be very influential on professional Human Resources researchers and leaders of organizations or companies in dealing with the development of AI (Artificial Intelligence) (Javaid et al., 2022).

The scope of this research will then explore the integration of AI (Artificial Intelligence) in Human Resource Management mechanisms in industries including manufacturing, finance, technology, and healthcare. This research will review the global perspective from both emerging and developed markets by using human resources from the recruitment process, managing employee potential, training, evaluating employee performance, developing AI, and creating regulations related to the company's work system. This research also aims to discuss the integration of AI (Artificial Intelligence) over the past ten years, looking at progress in the present and potential in the future (Zhang & Chen, 2024). The research on "Human Resource Management in the AI Era: Challenges and Opportunities" acknowledges limitations, including the rapid development of AI, perspectives, personal information security issues, cultural differences, emerging businesses, and external causes. The research intends to describe the current situation in general terms, but acknowledges that the environment can change quickly. The research acknowledges the importance of deep literacy in incorporating AI in human resource management, but also recognizes the limitations of providing an interpretive context. The scope of this research is designed to ensure focus and depth, while recognizing the limitations of AI technology.

The development of human resources has undergone major changes due to the metamorphosis of digital technology (Cherep et al., 2022). New skills and high qualifications that change according to the needs and development of the times have become crucial for workers in the changing times (Bhashanjaly, 2024). Therefore, applying artificial intelligence in human resource management opens up various tantalizing opportunities to make the work system more effective and efficient, and is interesting for further research (Kaushal et al., 2023). In addition, this discussion is also helpful in educating workers on how to prevent their performance from being eroded and replaced by new AI technologies that, if not utilized and dealt with properly, would backfire on the workers themselves. This research that reviews human resource management in the age of AI (Artificial Intelligence) at the stage of human resource management in the manufacturing sector has a limit to its discussion. It covers progressive changes in AI technology, favoritism, data privacy, cultural variants, new manufacturing, and external causes. This research also intends to describe whether external views can change quickly. An in-depth interpretation of the merging of Artificial Intelligence (AI) with Human Resource Management is needed, but the boundaries of the discussion regarding perspective are also used. This is the function of providing boundaries in this discussion so that the concentration and deepening of this material is not biased.

LITERATURE REVIEW

Artificial Intelegent (AI)

Artificial Intelligence in the employee selection process can make the process time-efficient and improve the quality of employee recruitment because of its ability to examine big data quickly and create comprehensive insights about applicants, thus minimizing subjectivity when making decisions (Balcioğlu & Artar, 2024). In the early days of Artificial Intelligence, many studies have proven that this technology can improve industrial mechanisms (Sasikumar et al., 2022). Regarding its ability to automate periodic assignments, Artificial Intelligence can increase functional optimization and allow leaders to focus on making more complex corporate choices (Tambe et al., 2019). This research explains that leaders who utilize Artificial Intelligence can increase crew capacity and create a company environment with breakthroughs. The utilization of Artificial Intelligence in examining company information supports the selection of the company's future steps through understanding the goals and industrial climate. Leaders can respond to transformation in a short time with significant data (Crossan et al., 1995).

This study question highlights how the Human Resources (HR) division can handle the obstacles arising from AI while ensuring a good combination of science and technology development and human interaction. Giacomin (2014) human-centered design theory proposes that AI development should be conducted to enhance human engagement, while social exchange science emphasizes the importance of a fair value balance between workers and AI mechanisms (Shah et al., 2024). Furthermore, this study's question investigates workers' views on the application of AI in HR procedures and their greatest fears and goals. Theories, including TAM, Psychological Ownership Theory (Asatryan & Oh, 2008), Job Characteristics Model (Wall et al., 1978), Psychological Contract Theory (Seeck & Parzefall, 2008), and Social Exchange Theory (Cook et al., 2013), provide the theoretical basis for understanding the complex interrelationship between AI behavior, expectations, and usability in the work environment (Batat, 2022).

Conceptualizing the Resource-Based View (RBV) Literature

The Resource-Based View (RBV) literature is a concept used in management science and industrial procedures to examine the resource mechanisms within companies that can potentially excel and be competitive sustainably (Coates & McDermott, 2002; Moderno et al., 2024). This concept states that competitive superiority depends on the company's competence to make management, improve, and utilize resources that are rare, valuable, difficult to imitate, and irreplaceable in existence (Resource Heterogeneity and Resource Immobility) (Morris et al., 2016). RBV has become an important cornerstone in corporate strategy development, as it provides a framework for evaluating internal strengths that competitors do not easily replicate. The Resource-Based View (RBV) has several main aspects (Shah et al., 2024), including: (1) Resources. The resource perspective literature views the company as a set of assets and competencies that can be used to achieve strategic goals (Kodua, 2019; Shah et al., 2024). Resources in question can take the form of tangible assets, such as working equipment, and non-physical assets such as trademarks, as well as capacities such as management (managerial) competencies. The existence and effective management of these resources can be an important foundation for achieving long-term performance of the company (Teece, 2014). The Resource-Based View (RBV) also focuses on the urgency of competencies from within the company to manage and explore resources appropriately (Connor, 2002). Capabilities can include the understanding, skills, and track record of employees, as well as appropriate business processes. In other words, capacity is an organized capability that enables companies to orchestrate their resources efficiently and innovatively (Lubis, 2022).

Furthermore, (3) Competitive Advantage, where RBV believes that rare and strategic resources and competencies can create opportunities for companies to generate sustainable competitive advantage (Oliver, 1997). This emphasizes that excellence does not only come from external factors, but more importantly, from the company's internal strengths. (4) Sustainable Excellence, a competitive advantage formed through internal resources and competencies that are rare and difficult to imitate, will be more difficult to destroy by business competitors (Coates & McDermott, 2002). When a company can maintain differentiation based on unique resources, the advantage can survive in the long term amid market pressure and high competition. Finally, (5) Implementation of the RBV Concept. RBV is utilized to examine the company's resources and competencies, determine its competitive advantages, and find appropriate strategies to explore them (Kodua, 2019). This implementation requires a deep understanding of internal strengths and alignment of business strategies with the company's potential, so that the company can remain adaptive and responsive to changes in the external environment. Thus, RBV not only provides a conceptual framework for assessing a company's internal strengths but also a strategic tool for designing a durable competitive advantage through the exploitation of unique resources and capacities.

The Concept of Human Capital

Human capital is an economic concept introduced by economist Theodore W. Schultz in the 1960s (Schultz, 1961). This concept emphasizes the importance of investment in educating, training, and developing human resources to obtain substantial economic benefits, both for individuals and all levels of society. Human Capital Theory sees human resources as assets that can increase competence and have significant marketability (Ployhart et al., 2014). This means that humans are not only seen as production factors, but also as dynamic entities that can be improved through systematic education, experience, and training. Human capital is a valuable resource in a country's economic development (Batra, 2009). In this context, sustainable economic development is strongly influenced by the country's ability to develop the quality of its human resources, because technological progress and work productivity are highly dependent on the intellectual capacity and skills of the workforce (Sima et al., 2020). This theory goes beyond physical infrastructure and assets with material value; it also involves the talents and competencies of the workforce. Thus, investment in education and workforce development is a strategic element in macroeconomic planning. This theory also explains that a person's competence and understanding are equivalent to an investment that can benefit individuals and society (Poquet & de Laat, 2021; Schultz, 1961). In Becker, (1962), human capital development is one of the main factors determining a country's economic growth, because educated and skilled individuals will be more productive, innovative, and able to create added value in every industrial sector. Therefore, this theory places humans at the center of socio-economic development and progress, which, if managed optimally, can become the main pillar of national competitiveness in the era of a knowledge-based economy.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a concept applied to computers, information, and attitudes to identify elements that play a role in how people accept and use science and technology (Davis, 1989). The theory was introduced by Fred Davis around 1989, and various adaptations and developments have been seen since its introduction. TAM emphasizes two important components, namely Perceived Ease of Use (PEU) and Perceived Usefulness (PU), which influence users' attitudes towards the development of science and technology. TAM initiates perceived ease of use and perceived function, which can influence behavior towards technology utilization (Abdullah et al., 2016). This behavior can then influence behavioral motives for utilizing technology and ultimately the actual use of technology. The expansion of TAM can be influenced by perceived ease and usefulness as well as other factors, including behavior, technical challenges, experience, and social factors (Prasetyo et al., 2025). By understanding the causes that can affect technology acceptance, companies can develop and use the latest technology effectively and efficiently (Davis, 1989).

Social Exchange Theory

This exchange concept is an analytical knife for discussing behavioral science, social psychology, and sociology (Cook et al., 2013). This discussion examines the interaction between a person and various communities regarding social relations, which refers to the concept of benefits and barter in a social context. This concept assumes that dominant individuals take attitudes with logic or ratios to optimally utilize benefits and minimize disadvantages when conducting social relations (Cook et al., 2013; Clarke et al., 2024). This concept examines social interactions that include disagreement, collaboration, marriage, and friendship. This concept can be used in all forms of relationships that have material value because every relationship will require costs and efforts in addition to the benefits obtained (Åström et al., 2022). The costs are not limited to money, but also to the energy expended and time spent. In every relationship, both parties need to exert time and effort so that the business relationship can be well established, in this case. The goal to be achieved is certainly a positive result (Cook et al., 2013).

Concept of Innovation Diffusion

This theory is a design utilized in the social field, especially in marketing, communication, and sociology, to examine why new breakthroughs or innovations spread in markets, audiences, or communities. This concept was brought and spread by Rogers (1976), a sociological researcher. Since then, this theory has become a fundamental concept in examining the stages of the spread of new breakthroughs and the acceptance of new concepts used in various issues, both in technology, agriculture, public health, and consumer behavior in the adoption of new technologies (Wolf, 2022). According to Rogers (1976), the innovation diffusion process includes five main stages: knowledge, persuasion, decision, implementation, and confirmation. Each individual or group goes through these stages before fully accepting or rejecting an innovation. In this context, innovation characteristics are also a determining factor in the speed of diffusion, which includes relative advantage, compatibility, complexity, trialability, and observability.

The uses of innovation diffusion include accelerating the adoption of innovations, increasing people's knowledge and awareness of innovations, maximizing the use of innovations and ensuring that they produce maximum benefits for society (Oldenburg & Glanz, 2008). The theory also helps policy makers, marketers, and community leaders to identify who falls into the categories of innovators, early adopters, early majority, late majority, and laggards, which are five categories of users based on how quickly they adopt innovations (Jahanmir & Lages, 2015; Wolf, 2022). In recent studies, innovation diffusion theory has also become increasingly relevant in understanding how digital technologies, such as artificial intelligence (AI), Internet of Things (IoT), and blockchain, are spreading across different industry sectors (Rejeb et al., 2022). The adoption of such technologies is highly dependent on innovative communication strategies and the role of change agents who drive behavioral change in organizations or communities (Greenhalgh et al., 2004). Therefore, innovation diffusion theory is not only a conceptual foundation in academic studies but also a practical tool in designing effective and inclusive innovation dissemination strategies.

Organizational Learning Concept

This concept is a design concept that is used in the context of management and groups to examine the process of groups learning, orienting, and honing the understanding that group education aims to improve the quality of their work (Crossan et al., 1999; Filho et al., 2016). This concept assumes that the group is an entity that can acquire, manage, and collect knowledge. Learning in a group context does not only occur individually, but becomes a collective activity that is embedded in the system, structure, and culture of the organization (Ivaldi et al., 2022). Learning in a group context is a way to reach a superior level and also be competitive in the context of an industry or business that can change at any time. Crossan et al., (1999) stated that the organizational learning process consists of four main processes: intuiting, interpreting, integrating, and institutionalizing, which occur at three levels, namely individual, group, and organization. This model shows that organizational learning is not just an accumulation of individual learning, but the result of complex interactions between these levels (Sturm et al., 2021).

This concept has an urgency to adapt to rapid market and environmental changes, help optimize the quality and competence of human resources, and increase the competitive advantage of a company and participate and maintain it in a rapidly changing business world (Dwikat et al., 2023). In a learning organization, there is a system that encourages the creation, acquisition, and transfer of knowledge, and modifies organizational behavior to reflect the new knowledge (Garvin, 1993). Furthermore, organizational learning is also linked to innovation and strategic change (Soomro et al., 2021). Organizations that can learn well have a higher tendency to produce innovative solutions, respond quickly to market dynamics, and create a work culture that supports cross-functional collaboration (Attah et al., 2024). This is a distinct advantage in the era of the digital industry and global complexity. In addition, this concept can ensure the company is able to face challenges in the business world and ensure that the company continues to lead in its industry, through increased collective awareness, critical reflection on internal practices, and the implementation of sustainable knowledge-based strategies (Caceres & Furlan, 2023; Senge, 1990).

Concepts of Human-Computer Interaction

Human-computer interaction is a science that concentrates on the reciprocal relationship that occurs between computers and their software and humans (Gondomar & Mor, 2021). It also includes the design of contact points that are likely to produce a targeted two-way communication pattern. The important purpose of this conceptualization is to improve the user's practice in dealing with this computer tool and to confirm that the user can interact with computer hardware or software with a more targeted, time-saving, and satisfying experience (ElSayary et al., 2025). Human-computer interaction is an important aspect of technology development because it ensures that a computer system is developed to meet the needs and goals of the user (Kashef et al., 2021). This concept encourages the creation of systems that are more user-friendly, effective, efficient, and less risky for all humans. This concept is also open to the evaluation and application of interfaces to facilitate computer users (Chromik & Butz, 2021).

Concept of Technology that Improves Efficiency

The concept of Technology that Improves Efficiency is a concept that examines the contribution of technology in improving operational efficiency in various sectors, both in the community and industry (Dalenogare et al., 2018). This concept departs from the assumption that technology can be utilized to simplify work processes, reduce operational costs, and produce various positive impacts such as reduced production costs, improved service or product quality, and increased overall productivity (Mithas et al., 2022). Technology can act as an enabler in optimizing workflows through automation, digitization of business processes, and data-driven decision-making. In the industrial context, automation has been proven to improve production line efficiency by reducing human involvement in routine and repetitive work. Robotic systems and smart sensors, for example, have been widely adopted in the manufacturing sector to increase production speed while maintaining quality consistency (Sahoo & Lo, 2022). Digital transformation is also a key component in this concept. The digital transformation process includes the integration of digital technology into all aspects of business and operations, including the use of Artificial Intelligence (AI), Internet of Things (IoT), and big data analytics. The application of AI in human resource management systems, for example, has shown effectiveness in simplifying the recruitment process, talent mapping, and specific needs-based employee training (Gill et al., 2022).

In addition, the concept is also relevant in the public and community sectors, where technology can be used to speed up public services, reduce bureaucracy, and promote transparency. The use of digital systems in civil registration, health, and education services can result in cost efficiencies and increased public satisfaction (Wandaogo, 2022). Recent studies have also shown that organizations that adopt efficiency-based technologies tend to be more resilient and adaptive in the face of global crises such as the COVID-19 pandemic (Zighan et al., 2022). The use of digital platforms and cloud-based work systems, for example, has helped many companies to maintain work productivity despite physical restrictions (Lal & Bharadwaj, 2016). Thus, this concept supports the implementation of automation, digital transformation, and the use of information technology in a more strategic and scalable manner, in an effort to improve overall organizational performance. The efficiencies achieved through technology adoption not only impact the cost aspect but also improve service quality, timeliness, data-driven decision-making, and long-term competitive advantage.

Work Experience Structure Concept

The work experience structure concept is an approach in human resource management that emphasizes the importance of designing, managing, and evaluating the overall employee experience at work (Plaskoff, 2017). This concept not only covers the physical aspects of work but also touches on emotional, social, and psychological aspects, such as job satisfaction, employee engagement, work-life balance, and experiences of interaction with managers and coworkers (Boccoli et al., 2023). A positive work experience has been shown to have a direct effect on increasing productivity, loyalty, and employee retention. Elements such as a supportive work environment, clear career development, open communication, and a fair reward system are important factors in structuring an effective work experience (Ismail et al., 2007; Sorn et al., 2023).

With an increasing focus on the holistic well-being of employees, work experience structures are becoming a strategic tool in employer branding and enhancing organizational competitiveness (Calvard & Sang, 2017).

Decision Support Scheme Concept

A Decision Support System (DSS) is an information technology-based system designed to support the decision-making process, both at the individual and organizational levels (Harper, 1993). This system integrates various important components such as data, models, and user interfaces to enable in-depth analysis of information and more targeted decision making (Sarker, 2021). In its structure, DSS has four main components, namely: Data Management System that functions to systematically manage and store internal and external data; Model Management System that presents various algorithms and predictive analysis to help formulate alternative decisions; User Interface Management System that provides access and convenience for users to interact with the system; and Knowledge Management System that provides experience-based insights and best practices as a reference in decision making. Along with technological developments, DSS is increasingly relevant in the era of digital transformation because it is able to utilize big data and artificial intelligence (AI) to produce faster, more accurate, and strategic decisions (Gupta et al., 2022). Currently, DSS is widely used by organizations for various purposes such as production planning, risk management, and operational performance evaluation, thus becoming an important element in improving the efficiency and effectiveness of organizational management (Pinter et al., 2021).

Boundary Management Concept

Boundary Management is a concept in work psychology and organizational behavior that describes how individuals manage the boundaries between their professional and personal lives, especially in the era of flexible and digital work (Derks et al., 2016). The increasing adoption of technology and the demands of working around the clock have made the boundaries between work and personal life increasingly blurred, leading to challenges such as digital fatigue, role conflict, and burnout (Kossek, 2016). In practice, there are three main strategies in boundary management, namely segmentation, where individuals strictly separate work and personal life activities; integration, which allows flexible blending of both aspects; and hybrid, which is a combination of the two and is used according to context and situational needs (Martineau & Trottier, 2024). Effective boundary management has been shown to positively impact mental health, increase work engagement, and support long-term productivity (Bakker, 2011). Given this urgency, many organizations are now implementing policies that support work-life balance, such as the right to disconnect, working time flexibility, and organizational interventions to create psychologically healthy workspaces (Galanti & Toscano, 2024).

Concept of Psychological Contract

A psychological contract is an unwritten understanding between an employee and an organization that reflects mutual perceptions of obligations, expectations, and commitments in the employment relationship (Alcover et al., 2017). Different from formal contracts that are legal and written, psychological contracts are implicit but have a significant influence on employees' work behavior, satisfaction, commitment, and loyalty to the organization (Manolopoulos et al., 2022; Rousseau, 1989). In general, the psychological contract is divided into two main forms: transactional, which is short-term and limited to material rewards such as salary and task performance; and relational, which is long-term oriented and involves emotional aspects such as mutual trust, support, and loyalty (Chen et al., 2024). A psychological contract breach can lead to negative consequences, including decreased motivation, increased turnover intention, and internal conflict. Therefore, transparent, consistent, and communicative human resource management practices are critical in building and maintaining a healthy psychological contract in the workplace. Recent research confirms that the renewal of psychological contracts that are adaptive to modern work dynamics, such as work flexibility and digital transformation, is crucial in maintaining employee engagement and performance (Gong et al., 2022; Malik et al., 2023; Löffert & Diehl, 2023).

METHODS

Human Resource Management is dominated by technological developments, especially in the context of artificial intelligence (AI). As AI increasingly enters the field of Human Resource Management, understanding the challenges and opportunities should be a key focus. Qualitative research efforts, especially those that utilize secondary data, can provide important insights into this changing environment. This paper examines the mechanisms by which qualitative research methods, as per the guidelines set out by Creswell & Creswell, (2017), can be appropriately used to explore Human Resource Management in the age of AI, emphasizing barriers and benefits. Qualitative research involves the collection and examination of non-numerical data that aims to achieve a comprehensive understanding of experiences, actions, and social issues. The systematic method developed by Creswell for qualitative research with secondary data provides an effective way to explore Human Resource Management in the age of AI. By formulating the research problem, determining appropriate secondary data sources, assessing the data quality, conducting in-depth analysis, and drawing significant conclusions, the researcher can gather important results about the barriers and benefits presented by AI in Human Resource Management.

RESULT

Artificial Intelligence (AI) in Human Resource Management (HRM)

The results of this study show that Artificial Intelligence (AI) has a significant contribution to human resource management (HRM) both now and in the future (Pillai & Sivathanu, 2020). AI is widely used in the recruitment process with the help of automated screening algorithms that can identify the best candidates based on competency and organizational culture fit (Jarrahi et al., 2021). In the aspect of performance appraisal, AI can analyze employee data in real-time to provide a more objective and data-driven evaluation. Additionally, in talent management, AI helps identify career development potential and devise customized training paths. Human resource planning is also becoming more precise with predictions of workforce needs based on historical trends and labor market data. AI supports fairer performance-based rewards by considering productivity metrics and employee contributions (Chatterjee et al., 2023). Finally, AI builds an inclusive work climate through employee sentiment analysis, early detection of burnout risks, and well-being monitoring. Nonetheless, the successful implementation of AI in HR is highly dependent on data integrity and ethical governance principles used by the organization (Deobald et al., 2022).

Matters to Consider for AI-integrated Human Resource Management: An Assessment of Ethical, Capable, and Conventional Realizations

The results of the study show that there is a profound shift in the way of thinking and ethical application in AI-integrated human resource management (Gong et al., 2022). The informants in this study revealed that while AI can improve operational efficiency and objectivity in HR practices, there are concerns about the emergence of algorithmic bias, indirect discrimination, and violation of individual privacy (Jarrahi et al., 2021). These issues raise the urgent need for a more in-depth assessment of the ethical realization and moral responsibility of implementing such technologies. The use of AI in the recruitment, performance evaluation, and talent management processes raises new discourses on fairness and equal access to employment opportunities. In the in-depth interviews conducted for this study, HR practitioners emphasized the importance of algorithm transparency, human involvement in final decisions, and strengthening internal regulations to ensure fair and unbiased treatment. Therefore, conventional approaches in HR are not necessarily abandoned, but rather need to be adaptively integrated with AI capabilities to create an efficient yet ethical HR management system (Nyberg et al., 2024). Furthermore, informants also expressed the importance of establishing a responsible and accountable AI governance system, as well as improving technological literacy for HR professionals to understand the limitations and risks of AI (Kambur & Yildirim, 2023). Thus, the integration of AI into human resource management must be accompanied by participatory, inclusive, and sustainable evaluative mechanisms.

The Role of AI in Human Resource Management: Revolutionary, with a Focus on Improving Worker Skills, Decision Making, and Experience

This research reveals that the application of artificial intelligence (AI) has substantially changed human resource management (HRM) practices, especially in improving operational efficiency, accelerating decision-making processes, and deepening understanding of worker characteristics and needs (Khan et al., 2024). Based on in-depth interviews with HR practitioners and organizational technology analysts, it was found that AI serves not only as an administrative tool but also as a strategic partner in supporting data-driven decision-making (Smallbone et al., 2022). AI, through advanced algorithms and graph-based computing, enables faster decision-making supported by pattern analysis from big data. In the context of talent management, AI helps identify the hidden potential of employees, map core competencies, and design more precise development strategies. Informants mentioned that the application of AI has shortened the stages of the recruitment process, improved accuracy in candidate selection, and supported the sustainability of overall organizational competencies. However, the results also highlight that while AI has great potential in reducing bias and increasing objectivity, favoritism can still occur if the input data used is unbalanced, discriminatory, or underrepresentative. Therefore, HR professionals need to have a deep understanding of how algorithms work and the importance of fair data curation to avoid reproducing systemic bias (Albaroudi et al., 2024).

Achieving Alignment: Minimizing Problems with AI in Human Resources

The findings of this qualitative study confirm that the integration of artificial intelligence (AI) in human resources (HR) management has the potential to significantly improve operational efficiency and workforce productivity (Brougham & Haar, 2018). Based on the results of in-depth interviews with HR practitioners and organizational policy makers, it is known that although AI offers many conveniences, its application also poses new challenges, especially in ethics and algorithmic justice (Deobald et al., 2019). Issues such as algorithmic bias, inequality in data-driven decision making, and lack of transparency in the evaluation process were highlighted (Tambe et al., 2019). Research participants expressed the importance of HR departments managing these challenges with a continuous monitoring-based approach. This includes conducting regular audits of AI systems, validating the accuracy of input data, and utilizing data visualization techniques that can be accessed and understood by a wide range of stakeholders (Esch & Black, 2019). Furthermore, while AI can simplify administrative processes and assist in big data-based decision-making, informants emphasized that AI cannot replace the human emotional and empathetic elements of building interpersonal relationships in the work environment. Values such as understanding, mutual communication, and emotional support remain important dimensions that cannot be fully automated (Schreiber et al., 2024). Thus, to achieve harmony between technological efficiency and human values, organizations need to develop a hybrid approach that combines the analytical capabilities of AI with human sensitivity in HR management.

DISCUSSION

Acquisition of Superior Competencies

Acquisition of superior competencies is a key human resource management utility (Pillai & Sivathanu, 2020). AI is already producing substantial discoveries in the context of the development of this science. AI and its algorithms, as stated by Pillai & Sivathanu, (2020) are useful for selecting CV summaries, generating initial Q&A, and analyzing the best candidates for a profession (Chérif et al., 2021). AI algorithms can find a large number of CV summaries in a short time, select criteria, and create probabilities of candidate excellence based on historical data. These advantages can shorten the time and steps needed to recruit candidates (Lee, 2011). Human resource specialists can concentrate more on other, more essential work (Tursunbayeva et al., 2017). Artificial intelligence (AI) has shortened the introduction and training stages of workers, and this has increased the impression of all new workers in the company (Zhang & Tao, 2021). AI-enabled chatbot systems have made the substance of customized introductions and real-time responses to workers' questions, reducing time and human resources for the human resources division (Majumder &

Mondal, 2021). AI has reviewed training data and responded quickly, creating the possibility for workers to constantly improve their competencies (Wang & Siau, 2019). Artificial intelligence (AI) also changes the realization of human resources by shortening stages, increasing optimality, and improving workers' impressions (Tursunbayeva et al., 2017). AI makes repetitive work automatic, helping human resource specialists to concentrate on more essential work (Lee, 2011). AI as a Chatbot enabler contributes to quick support and response to workers' queries in general (Majumder & Mondal, 2021). This minimizes human intervention (Zhang & Tao, 2021). AI can be relied upon to examine workers' competency data as well as critiques and suggestions to recognize modes, making it easier for human resource specialists to make targeted decisions (Wang & Siau, 2019). However, AI and its subjective algorithms may create an exclusive realization of the world of work, making existing class differences visible, and eliminating qualified candidates from the aspects of social and economic class, ethnicity or race, and gender (Raghavan et al., 2020).

Work Competency Assessment

Artificial intelligence (AI) has changed the work assessment efforts undertaken in a company (Wang & Siau, 2019). Armed with AI tools, human resources divisions can examine worker competencies by data (Majumder & Mondal, 2021). This is to obtain important results (Pillai & Sivathanu, 2020). Data analysis based on AI can unearth modes and patterns in company performance and enable the human resources division to deliver interactions to workers appropriately and quickly (Zhang & Tao, 2021). This can improve workers' competence, increase productive power, and contribute to a culture of continuous evaluation (Lee, 2011). AI-based reviews can help human resources divisions discover which areas need upgrading (Wang & Siau, 2019). AI algorithms can unearth subjectivity or inconsistencies in improvement qualifications (Raghavan et al., 2020). In addition, improvements and fairness can be guaranteed to eliminate favoritism (Raghavan et al., 2020). AI systems can also respond quickly to interactions and suggestions for managers, and make precise decision-making probabilities regarding workers' performance improvement and development (Zhang & Tao, 2021). It also encourages the formation of supportive company areas (Tursunbayeva et al., 2017). AI technology can also examine data regarding worker competencies (Majumder & Mondal, 2021). Another is that it can generate highly objective knowledge for managers and create monitored upgrading and training targets (Pillai & Sivathanu, 2020). AI has another skill, which is detecting the frequency of worker interventions as well as spotting signs of fatigue and enabling quick action (Wang & Siau, 2019). However, relying on AI instead of humans can result in a lack of empathy and human interaction (Raghavan et al., 2020). This has adverse effects on productive power and morality (Zhang & Tao, 2021). AI tools and human interaction must be balanced, and this has the effect of creating an accomplished and empathetic corporate environment (Lee, 2011).

Planning Worker Candidates

Planning worker candidates plays a key role in companies, ensuring that superior quality workers achieve the company's main goals (Bowen & Lawler, 1992; Brock & von Wangenheim, 2019). AI forecasting skills play a major role in this (Jarrahi et al., 2021). AI can be utilized to forecast the number of workers needed in the future and explore differences in competencies (Margherita, 2021). Thanks to the role of analyzing historical employee data, external causes, and market direction, AI can ease the work of human resource specialists to make data-driven decisions about employee retention, selection, and training (Sivathanu & Pillai, 2018). AI can help organizations recognize possible barriers and benefits in workforce planning by examining data related to employee turnover, performance, and engagement (Garcia & Osca, 2021). This data can be used to design specific tactics to retain employees and develop talent (Premuzic et al., 2017). In addition, AI can make it easier for human resource professionals to find talented employees for leadership positions or vital roles, giving organizations the opportunity to actively prepare and sustain resources to lead in the future (Tambe et al., 2019). AI's prediction skills provide companies with powerful tools to maximize workforce qualification design, ensure that the right people are in the right positions, and support sustainable success (Deobald et al., 2019). For example, global companies are leveraging AI for staff performance data analysis, proposing promotions, and offering customized training opportunities (Bersin, 2018). AI technology can respond directly to interactions and performance appraisals, fostering a culture of education and long-term development (Brougham & Haar, 2018). However, relying too much on AI to manage talent can override human instincts and compassion, which are instrumental in assessing a person's development and the developmental needs of each employee.

Talent Management

Talent management is another aspect where artificial intelligence has emerged as a valuable resource (Tambe et al., 2019). AI technology can detect highly competent workers and offer customized development plans (Chatterjee et al., 2023). Based on the analysis of many data types, including performance appraisals, training data, and worker responses, AI can recognize talents with the most significant probability of advancement and suggest specific tactics for their growth (Chatterjee et al., 2023). This not only benefits workers but also helps companies build successors for the future. AI can ease the talent acquisition process by processing big data, finding the most suitable candidates, and conducting the initial selection, which shortens the time for HR professionals (Lee, 2011). It can also foster a more supportive and varied work environment by minimizing subjectivity that may go unnoticed in the selection phase (Sinha & Lee, 2024). AI can obscure population factors and support the creation of a diverse workforce (Budhwar et al., 2023). However, AI settings also have the potential to unintentionally reinforce existing discrimination in training archives, which can lead to disparities and complicate efforts to create a diverse and inclusive workforce. Innovations in algorithmic fairness and techniques such as bias reduction can contribute to reducing these problems and supporting diversity and inclusion in the workforce (Budhwar et al., 2023).

Success and Rewards

AI contributions also exist in realizing more equitable rewards and benefits in human resource management (Kyriakidou et al., 2025). Thanks to the role of reviewing workers' compensation data, AI can discover personal differences and subjectivity in the context of wage design (Budhwar et al., 2023). AI is a suitable effort to eliminate wage inequality within the labor caste. AI can create knowledge about the realization of fairness-principled wage receipts, alleviate the work of companies to equalize the reward tactics of workers to match the market standardization and net worth assessment from within the company (Kyriakidou et al., 2025). It supports openness and equity in decision-making about rewards or wages (Budhwar et al., 2023). AI can encourage variety and engagement in human resource management by analyzing worker data, recognizing trends, and recognizing subjectivity in the selection and hiring stages (Chatterjee et al., 2023). This data-driven concept supports equality in teams with superior competencies. However, leaving all tasks irresponsibly to AI may lead to the realization of highly subjective worker selection and minimize the role of human compassion (Bankins & Formosa, 2023). AI can minimize subjectivity with variant data, increase the acceptance tactics, and worker retention, as well as corporate competence (Budhwar et al., 2023). It can also release human resources from repetitive work, increasing the probability of human resource specialists concentrating on essential work.

Future Possibilities

It is likely that future developments in the world of human resource management will accelerate (Azeez et al., 2024). Newer tools such as natural language processing (NLP), machine learning, and probability analysis will play a major role in enhancing the performance of AI in human resource management (Pruneski et al., 2023). AI-driven virtual assistants and chatbots will play an important role in providing answers to workers' questions, recognition, and support in real time. Furthermore, AI can also analyze workers' feelings. In addition, AI can also increase the role and success of workers. AI can assist in talent acquisition by automating the screening and onboarding stages, which can cut time and resources for HR specialists. In addition, AI can also provide precise insights into workers' competencies, which will support more effective performance management and development activities (Tambe et al., 2019). AI also plays an important role in the structuring and maximization of workers, with the opportunity to help companies manage talent more efficiently and make appropriate decisions regarding hiring, coaching, and success strategies (Chérif et al., 2021). With the development of AI, this technology can examine worker competency data to find traits that support teams and individuals who excel, which can be used to design more targeted coaching activities or adapt recruitment strategies. AI can also assist HR in forecasting future talent needs by examining historical data on turnover frequency and worker competency parameters, allowing companies to play a greater role in addressing staffing shortage opportunities and ensuring a smooth process for strategic success. However, relying on AI alone to find highly qualified individuals and teams may miss out on immeasurable qualities such as leadership skills and workforce development (Garibay et al., 2023). In addition, historical data cannot always accurately predict future talent needs, especially due to external causes such as market changes or changes in industry culture.

Making Decisions

AI's analytical skills play a major role in easing the decision-making stage of human resource management (Tambe et al., 2019). This allows companies to gain comprehensive knowledge about their marketing goals and implement data-driven marketing tactics (Chatterjee et al., 2023). Then, the ability to analyze data in AI can make companies gain valuable knowledge about which areas need upgrading in the human resource management stage. For example, the areas of recruitment, competency assessment, and talent management. Good utilization of AI analysis can have an impact on effective decision-making skills and company achievements and profits, as well as positive impressions from workers (Jarrahi et al., 2021). AI support in the process of analyzing data can gradually increase the role and resilience of workers by finding patterns and modes of positive impression, drive, and productive power (Zong & Guan, 2024). This has the opportunity to make HR specialists play an active role in solving problems and implementing tactics to improve the lives of company workers. Thanks to AI, periodic human resource tasks can be automated, such as wage management and benefits management, minimizing administrative stress and increasing usability. The incorporation of AI in human resources can create more empowered workers and increase worker satisfaction, as workers will feel supported and cared for (Malik et al., 2023). For example, AI can recognize symptoms of fatigue or estrangement that occur in groups or individuals. This has the potential to make troubleshooting by HR specialists happen faster and to take immediate action. AI can also shorten the hiring process by providing resume analysis and finding highly qualified candidates based on company qualifications (Tambe et al., 2019). However, AI algorithms may not fully detect major causes, which may make the process of error and role discovery ineffective (Jarrahi et al., 2021). However, AI algorithms can be further improved and trained to better understand root causes, minimize subjectivity in the hiring process, and ensure in-depth assessment of candidates. Incorporating artificial intelligence (AI) in human resource management (HRM) is a knife with two edges. It is tantalizing in terms of improving usability, but at the same time, it presents obstacles in terms of ethics, skills, and keeping workers in touch. To ensure a harmonious collaboration between science, technology, and human aspects, human resource divisions need solutions to resolve these barriers (Tursunbayeva et al., 2017). This paper explores the human resources division's efforts to prevent these barriers by gaining knowledge from recent papers, journals, and proceedings that allow for citation.

The use of artificial intelligence in a responsible way in human resource management is a growing area that requires attention (Tambe et al., 2019). It is important to address algorithm unfairness by incorporating elements of inclusion and fairness in the machine training process to mitigate the problems posed by advanced artificial intelligence. Human resources departments need to actively take steps to address existing algorithmic inequities as well as act to prevent similar problems in the future (Tambe et al., 2019). Approaches to reducing and preventing artificial intelligence inequities in HR, such as placing employee well-being and ethical considerations as priorities, should be adopted in HR policies and practices. Organizations should place diversity and inclusion as a key focus within their work teams to build a fair AI system. This can be done by actively engaging individuals from diverse backgrounds, implementing effective monitoring and auditing systems, and investing in ongoing training for staff (Saeidnia, 2023). HR departments can also promote fairness and equity in AI systems. Regular audits can help detect inequities in AI algorithms, which can then be addressed by data scientists and developers (Murikah et al., 2024). Diversity and inclusion training can help recruitment managers understand and reduce inequities during the candidate assessment process. Anonymous resume screening processes can also contribute to reducing unconscious bias. However, artificial intelligence systems may produce bias due to the data used in their training.

CONCLUSION

AI is transforming Human Resources, from the talent search process to the management of rewards and benefits. As companies begin to use AI systems, HR professionals need to adapt and use the tools to refine their practices, improve the quality of provisions, and realize a more efficient HRM environment with a focus on workers. The adoption of AI in Human Resources reflects a shift to a more strategic and data-driven way of managing human resources. However, it also presents challenges, such as ethical issues, the need for new skills, and shifts in existing HR practices. To successfully meet these challenges, organizations need to ensure that the use of AI is done responsibly, adhering to ethical decision-making principles, developing skills, and adapting to changing norms in the HR world. Responsible use of AI not only improves organizational effectiveness but also creates a more ethical and inclusive work environment. The continued growth and innovation in the use of AI in HRM point to a promising future where organizations can achieve higher efficiency, make more informed decisions, and increase employee satisfaction through a balance between technology and the human touch. HR departments need to address biases in algorithms, apply ethical principles in decision-making, offer skills development opportunities, and utilize AI as a useful addition.

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