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The Role of Artificial Intelligence in Human Resource Management: Implications for Employee Motivation, Performance, and Technology Acceptance

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A R T I C L E I N F O

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A B S T R A C T

The integration of Artificial Intelligence (AI) into Human Resource Management (HRM) has transformed traditional HR functions, optimizing processes such as recruitment, selection, training, development and learning, performance management, and employee engagement. While AI offers efficiency and data-driven decision-making, its impact on employee motivation and workplace performance remains a subject of ongoing debate. This study examines the relationship between AI-driven HRM practices and employee motivation, focusing on the mediating role of AI acceptance. Using a quantitative research design, data was collected from 150 respondents across multiple industries, analyzing key variables such as AI-driven feedback, intrinsic and extrinsic motivation, and job performance. Findings indicate that AI adoption in HR positively influences motivation and performance, but this relationship is significantly mediated by employees' acceptance of AI technologies. The study highlights the importance of AI transparency, user-friendliness, and ethical implementation in fostering a motivated and high-performing workforce. Practical implications suggest that organizations should adopt a human-centered approach to AI integration, balancing technological efficiency with employee empowerment. Future research should explore longitudinal effects and industry-specific AI adoption trends.

1. Introduction

The rapid advancement of Artificial Intelligence (AI) has significantly transformed various sectors, including Human Resources (HR). AI-driven tools are increasingly utilized to optimize recruitment, selection, training, and performance management (Stone et al., 2015). While these technological innovations aim to enhance efficiency and decision-making processes, their impact on employee motivation and engagement remains an area of active academic inquiry (Brynjolfsson & McAfee, 2017). Organizations that seek to balance technological integration with employee well-being must understand how AI-driven HR practices influence intrinsic and extrinsic motivation (Glikson & Woolley, 2020).

The integration of Artificial Intelligence (AI) in Human Resource Management (HRM) is revolutionizing various HR functions, including recruitment, performance management, and employee engagement (Ganatra & Pandya, 2023; Sadeghi, 2024). AI-powered tools improve efficiency, minimize bias, and support data-driven decision-making (Madanchian et al., 2023; Sundari et al., 2024). While AI provides numerous advantages, such as enhanced operational efficiency and tailored employee experiences, it also raises concerns about job security, fairness, and privacy (Bharadwaj, 2024; Sadeghi, 2024). Effective AI implementation in HR requires a balanced approach that emphasizes employee well-being, upholds ethical practices, and promotes human-AI collaboration (Manoharan, 2024; Islam, 2024). Organizations must tackle challenges like skill gaps, resistance to change, and algorithmic biases through strategic planning, continuous training, and strong data governance (Islam, 2024; Nyathani, 2021). As AI technologies advance, their applications in HR are expected to grow, offering more sophisticated tools for optimizing human capital management (Manoharan, 2024).

Motivation is a key determinant of employee performance and organizational success. Traditional motivation theories, such as Self-Determination Theory (Deci & Ryan, 2000), emphasize the importance of autonomy, competence, and relatedness in fostering workplace engagement. However, the integration of AI introduces new dynamics, potentially reshaping motivational drivers. Automated feedback systems, AI-driven

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performance evaluations, and digitalized HR processes might enhance motivation by providing real-time support, yet they may also undermine motivation by reducing human interaction and perceived autonomy (Davenport & Ronanki, 2018; Koopmans et al., 2013).

Recent research underscores the transformative impact of AI on employee motivation and HR practices. Self-Determination Theory (SDT) remains a vital framework for understanding motivation, focusing on autonomy, competence, and relatedness (Chong & Gagné, 2019; Guo, 2023). AI integration in HR can support these needs through personalized experiences and real-time feedback (Arokiyaswamy et al., 2024; Sundari et al., 2024). However, employee perceptions of AI systems play a significant role in shaping motivation and behavior (Edwards et al., 2024). AI-driven feedback is sometimes perceived as less accurate and motivating compared to human feedback, influenced by social distance (Hein et al., 2024). Despite this, AI in performance management provides advantages such as unbiased assessments and customized development plans (Nyathani, 2023). While AI adoption in HR enhances operational efficiency and strategic decision-making, challenges like employee resistance and ethical concerns persist (Ganatra & Pandya, 2023). Striking a balance between technological solutions and human-centered strategies is essential for optimizing the benefits of AI in workplace motivation.

Despite increasing academic interest in AI applications within HR, research on its direct impact on motivation and job performance remains scarce (Jarrahi, 2018). The novelty of this study consists in aiming to bridge this gap by investigating how AI-driven motivation strategies affect employee engagement and satisfaction. Specifically, it examines whether AI-generated feedback enhances workplace performance, whether HR automation promotes intrinsic motivation, and how employees' acceptance of AI mediates the link between digitalization and motivation (Vrontis et al., 2021).

Research Hypotheses:

H1: Implementing AI in HR motivation processes positively influences employees' intrinsic motivation (Deci & Ryan, 2000).

H2: AI-generated automated feedback enhances job performance (London & Smither, 2002).

H3: HR motivation processes contribute to improved workplace performance (Koopmans et al., 2013).

H4: Employees' acceptance of AI mediates the relationship between digitalization and motivation (Davis, 1989).

The structure of this paper is as follows: Section 2 presents a literature review covering the theoretical foundations of AI in HR, motivation theories, and performance management. Section 3 outlines the research model, methodology, and data collection process. Section 4 reports the empirical findings, followed by Section 5, which discusses theoretical and managerial implications. Finally, Section 6 concludes the study, summarizing key contributions and potential avenues for future research

2. Literature review

The increasing role of Artificial Intelligence (AI) in human resource management (HRM) has generated substantial interest in both academic and managerial circles. AI is recognized as a key enabler in modern HR practices, facilitating talent acquisition, employee engagement, and performance management (Vrontis et al., 2021). However, AI's influence extends beyond administrative efficiency, as its role in shaping workplace motivation and job performance has become a focal point of contemporary research (Glikson & Woolley, 2020). The integration of Artificial Intelligence (AI) into Human Resource Management (HRM) has led to a paradigm shift in organizational practices, impacting motivation, performance, and employee acceptance of digital transformation. Existing research has examined the implications of AI-driven HRM, but gaps remain in understanding how AI influences intrinsic motivation, performance, and employee engagement.

2.1. Implementing AI in HR motivation processes positively influences employees' intrinsic motivation

Artificial Intelligence has been increasingly integrated into HRM processes to enhance the motivation of employees by fostering personalized career development, automating repetitive tasks, and optimizing decision-making processes (Jarrahi, 2018). The Self-Determination Theory (SDT) proposed by Deci and Ryan emphasizes the significance of autonomy, competence, and relatedness in fostering intrinsic motivation (Deci & Ryan, 2000). AI-driven HR tools align with this framework by providing employees with access to customized career development plans, training opportunities, and performance assessments tailored to their strengths and areas for improvement (Stone et al., 2015).

A growing body of research has emphasized that AI-driven HRM systems can enhance intrinsic motivation by fostering a more personalized and efficient workplace (Stone et al., 2015). AI-powered systems can provide employees with tailored training programs, real-time feedback, and personalized career development pathways, aligning with the principles of Self-Determination Theory (SDT) (Deci & Ryan, 2000). This personalization enhances competence and autonomy, two crucial elements of intrinsic motivation (Jarrahi, 2018).

Despite these benefits, some scholars argue that AI can diminish intrinsic motivation if not implemented properly. Employees may perceive AI-driven decision-making as reducing their autonomy, leading to feelings of alienation and decreased motivation (Davenport & Ronanki, 2018). Therefore, while AI can significantly contribute to enhancing intrinsic motivation through personalized learning and development programs, organizations must ensure that AI tools are designed to complement, rather than replace, human decision-making processes.

However, some studies indicate potential drawbacks. While AI systems provide efficiency, they may reduce human interaction, leading to a perceived loss of control and diminishing intrinsic motivation (Davenport & Ronanki, 2018). Thus, AI should complement rather than replace human oversight to maintain a balance between automation and employee autonomy. The challenge lies in integrating AI in a way that enhances motivation while preserving the psychological needs that foster engagement and job satisfaction (Glikson & Woolley, 2020).

On the basis of the reviewed literature, AI-driven HRM practices have the potential to positively impact intrinsic motivation when properly implemented. Thus, we propose the following hypothesis: *H1: Implementing AI in HR motivation processes positively influences employees' intrinsic motivation.*

2.2. AI-generated automated feedback enhances job performance

The role of feedback in employee performance has been widely studied in organizational behavior, with research suggesting that timely, objective, and relevant feedback is essential for improving employee productivity and engagement (London & Smither, 2002). AI-driven feedback mechanisms can provide real-time, data-driven insights into employee performance, offering personalized recommendations for improvement and enabling continuous learning (Glikson & Woolley, 2020).

Automated feedback systems have the potential to improve employee performance by eliminating biases inherent in human evaluations and ensuring a standardized approach to performance assessment (Koopmans et al., 2013). However, the effectiveness of AI-generated feedback depends on employees' perceptions of its fairness and relevance. If employees perceive AI-driven evaluations as impersonal or overly mechanistic, they may resist incorporating feedback into their daily work practices (Brynjolfsson & McAfee, 2017). Thus, while AI-generated feedback has the potential to enhance job performance, its implementation must be accompanied by human oversight and continuous adjustments based on employee feedback to maintain engagement and trust.

Performance feedback is a cornerstone of employee development, and AI-driven feedback systems offer significant advantages in terms of accuracy, timeliness, and customization (London & Smither, 2002). Research suggests that automated feedback can enhance performance by providing data-driven insights, eliminating subjective biases, and allowing for continuous improvement (Glikson & Woolley, 2020).

However, the effectiveness of AI-generated feedback depends on how it is perceived by employees. While some employees view AI-driven feedback as objective and constructive, others perceive it as impersonal and detached from contextual human factors (Koopmans et al., 2013). Moreover, Brynjolfsson and McAfee argue that reliance on AI-driven performance evaluation could create resistance if employees feel reduced agency in their own professional development. For AI-driven feedback to be effective, organizations must integrate it with human judgment, ensuring that employees view it as an enabler rather than a constraint. On the basis of the reviewed literature, AI-generated feedback can enhance job performance when perceived as fair and constructive. Thus, we propose the following hypothesis: *H2: AI-generated automated feedback enhances job performance.*

2.3. HR motivation processes contribute to improved workplace performance

Motivation remains a key determinant of workplace performance, with HR processes playing a critical role in fostering employee engagement and productivity (Koopmans et al., 2013). AI-driven HR strategies offer innovative ways to enhance motivation by leveraging predictive analytics, personalized training, and automated recognition systems (Vrontis et al., 2021). These tools can help managers identify high-performing employees, predict potential disengagement, and implement targeted interventions to maintain motivation and productivity.

Nevertheless, the effectiveness of AI-driven HR motivation strategies depends on their integration with broader organizational culture and leadership styles (Stone et al., 2015). Employees are more likely to embrace AI-enhanced HR processes when they perceive them as supportive rather than as mechanisms for increased surveillance or micromanagement. As a result, AI-driven motivation strategies must be designed to align with organizational goals, ensuring that they enhance rather than disrupt traditional HR functions.

HRM strategies play a pivotal role in enhancing workplace performance, and AI-driven solutions are reshaping these strategies by providing real-time insights into employee behavior, predicting engagement trends, and tailoring motivational approaches (Vrontis et al., 2021). Predictive analytics, for example, can identify early signs of disengagement and recommend personalized interventions to retain employee commitment and enhance productivity (Koopmans et al., 2013).

Nonetheless, AI-driven HR processes must be aligned with organizational culture to achieve the desired impact. Stone et al. highlight that while AI provides efficiency, its effectiveness depends on how well it integrates with leadership styles and organizational communication (Stone et al., 2015). If AI systems are perceived as tools for surveillance rather than empowerment, employees may resist their implementation, diminishing the potential performance benefits. Therefore, AI's role in HRM must be carefully curated to balance automation with human-centric leadership practices. On the basis of the reviewed literature, HR motivation processes can significantly contribute to workplace performance when effectively integrated. Thus, we propose the following hypothesis: *H3: HR motivation processes contribute to improved workplace performance.*

2.4. Employees' acceptance of AI mediates the relationship between digitalization and motivation

The successful implementation of AI-driven HRM strategies is contingent upon employees' willingness to accept and adapt to AI technologies (Davis, 1989). The Technology Acceptance Model (TAM) posits that perceived usefulness and ease of use are key determinants of technology adoption in the workplace. Employees who perceive AI tools as enhancing their efficiency and job satisfaction are more likely to integrate them into their daily work processes, thereby improving overall motivation and performance (Davenport & Ronanki, 2018).

However, resistance to AI adoption remains a major challenge for organizations seeking to leverage digitalization for HRM improvements. Concerns regarding job displacement, privacy, and algorithmic biases can undermine employees' trust in AI-driven HR processes (Glikson & Woolley, 2020). Organizations must address these concerns by fostering transparency, offering continuous training, and involving employees in AI implementation decisions. When employees feel empowered in the digitalization process, they are more likely to accept AI tools as beneficial, ultimately mediating the relationship between digitalization and motivation (Vrontis et al., 2021).

By synthesizing insights from existing literature, this section establishes a theoretical and empirical foundation for the current study. The next section will present the research methodology, outlining the study design, data collection process, and analytical techniques employed to test the proposed hypotheses.

The successful adoption of AI in HRM depends on employee acceptance and trust in digital systems (Davis, 1989). The Technology Acceptance Model (TAM) posits that perceived usefulness and ease of use determine whether employees integrate AI-driven tools into their daily workflows (Davenport & Ronanki, 2018). Employees who perceive AI as an enabler of efficiency and career growth are more likely to embrace digitalization and experience enhanced motivation (Glikson & Woolley, 2020).

Conversely, resistance to AI adoption remains a persistent challenge. Concerns regarding algorithmic bias, job security, and ethical considerations may hinder employees' willingness to engage with AI-driven HRM systems (Vrontis et al., 2021). Transparency in AI decision-making, continuous training, and involving employees in AI implementation strategies can mitigate resistance and foster a culture of digital trust. By positioning AI as a tool for empowerment rather than control, organizations can enhance motivation and facilitate smoother digital transitions (Brynjolfsson & McAfee, 2017). On the basis of the reviewed literature, employee acceptance of AI plays a mediating role in the relationship between digitalization and motivation. Thus, we propose the following hypothesis: *H4: Employees' acceptance of AI mediates the relationship between digitalization and motivation.*

This review consolidates existing research on AI-driven HRM, highlighting both its potential and its limitations. While AI enhances motivation through personalized feedback and predictive analytics, its effectiveness hinges on employee perceptions and organizational culture. Theoretical contributions of this study lie in refining our understanding of how AI mediates motivation and performance, bridging gaps in current literature on AI integration in HRM.

Empirical contributions stem from analyzing real-world implications, offering insights into best practices for AI adoption in HR. By integrating AI with traditional motivation frameworks and HR strategies, organizations can optimize digital transformation while maintaining employee engagement.

3. Methodology

This section describes the research strategy, data collection methods, and techniques used to analyze the impact of artificial intelligence (AI) on employee motivation and job performance. The main objective of the study is to investigate the relationships between the use of AI in human resources, automated feedback, employee acceptance of AI, employee motivation and job performance.

3.1. Research design

The research design is quantitative, cross-sectional and explanatory, aiming to identify causal relationships between the variables analyzed. The study adopts a deductive approach, starting from theoretical hypotheses validated in the literature, which are subsequently tested by analyzing the empirical data collected.

The research was conducted online using a structured questionnaire distributed to a sample of 150 respondents. This method was chosen to ensure a broad coverage of different industries and levels of professional experience, facilitating the collection of data relevant to the purpose of the study. Given the explanatory objective of the study, a questionnaire survey was chosen to measure employees' perceptions in relation to the use of AI in HR, its acceptance, impact on motivation and performance. The questionnaire was designed to cover all relevant dimensions of the research. The items were adapted from previously validated scales in the literature, including TAM (Davis, 1989), WEIMS (Deci & Ryan, 2000), Job Performance Scale(Koopmans et al., 2013) and Employee Feedback Scale (London & Smither, 2002) (Figure 1).

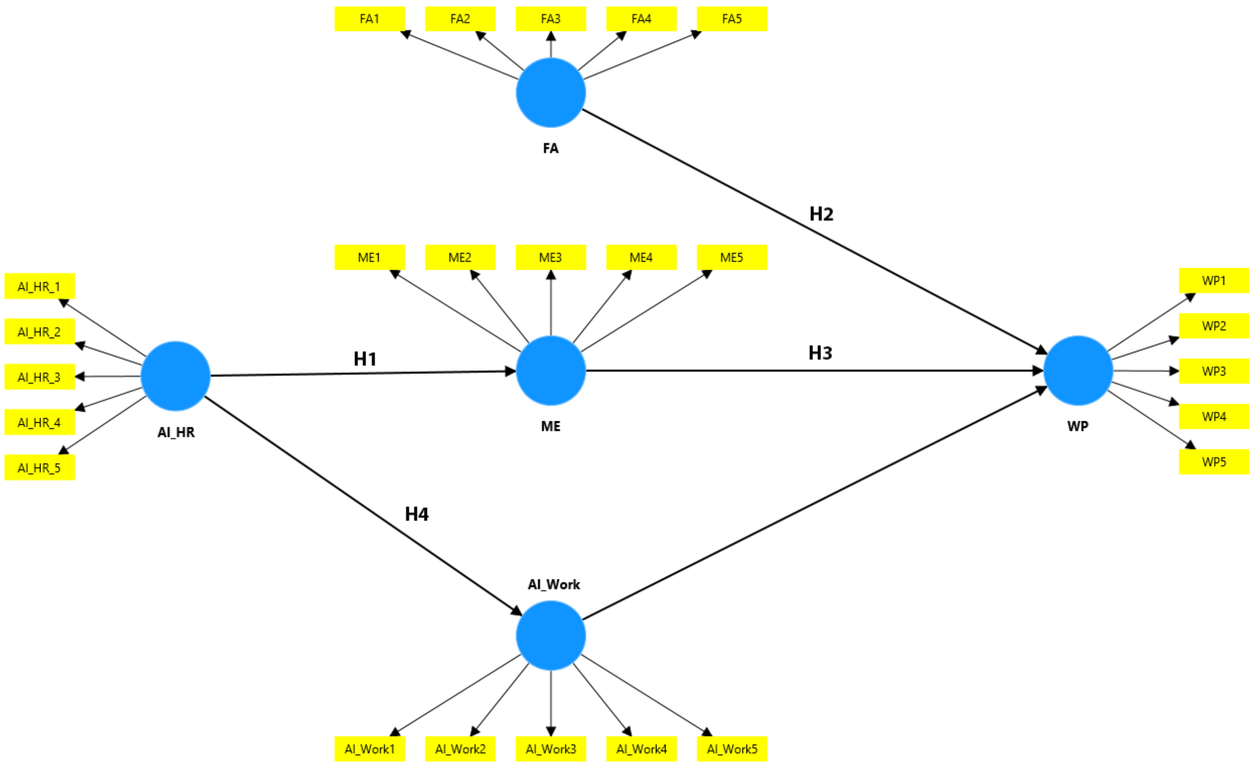

Figure 1. Research design

Its structure included separate sections for demographics, use of AI in HR, employee motivation, job performance and acceptance of AI. The questionnaire was distributed via online platforms, including professional networks, social media groups and direct emails. Participants were selected using conventional sampling with their exposure to AI-based systems in HR as the main criterion. Data was collected over a period from October 2024 to February 2025, ensuring a sufficient volume of respondents for robust statistical analysis. The proposed questionnaire is structured into five key sections, each aimed at investigating specific aspects related to the use of artificial intelligence (AI) in HR and its impact on different professional dimensions. The first section, entitled Demographic and Occupational Data, aims to collect basic information about the respondents, including variables such as age, gender, educational level and accumulated work experience, in order to allow a contextualized and relevant analysis of the data. The second section, The Use of AI in HR, focuses on assessing the extent to which AI technologies have been integrated into HR processes such as recruitment, selection, appraisal and training, drawing on the Technology Acceptance Model (TAM) developed by Davis (Davis, 1989). Next, the section titled Employee Motivation, based on the Work Extrinsic and Intrinsic Motivation Scale (Deci & Ryan, 2000), explores the extent to which the use of AI influences employee commitment, intrinsic and extrinsic motivation, and professional development. The fourth section, Job Performance, draws on the Job Performance Scale (Koopmans et al., 2013) to measure efficiency, productivity, and decision-making ability under the influence of AI implementation in various organizational processes. Finally, the last section, AI Acceptance and Automated Feedback, inspired by the Employee Feedback Scale (London & Smither, 2002), investigates employees' perceptions towards the use of digitized feedback and the degree to which it is accepted as a legitimate method of evaluating their performance. This comprehensive questionnaire aims to provide a holistic and comprehensive perspective on the impact of AI on the work environment, integrating critical variables that influence both organizational performance and individual employee satisfaction.

3.2. Sample description

The use of age categories in analyzing the impact of artificial intelligence (AI) on employee motivation is based on theoretical models in the field of career development and empirical research on organizational behavior. The segmentation of respondents into age groups (18-25, 26-35, 36-45, 46-55 and 56-65 years) reflects the distinct stages of the career path as defined by theorists such as Super and Hall, providing an appropriate tool for studying differences in motivation, attitudes and relationship with technology (Hall, 2002; Super, 1980). Each period in the working life is marked by specific features – from initial exploration of the labor market and the accumulation of foundational skills (18-25 years) to advanced leadership responsibilities

(Savickas, 2002) and preparation for retirement (56-65 years) – influencing both the way individuals engage in their activities and their openness to technological innovations (Arthur & Rousseau, 2021; Kooij et al., 2007; London & Smither, 1999; Warr, 2008). Furthermore, the literature, including generational research, highlights that perceptions of emerging technologies such as AI differ significantly across professional generations: younger people are generally more open but may feel anxious about its impact on job security, while older employees, although reluctant, may recognize the benefits of AI in streamlining processes or reducing repetitive tasks (Lyons & Kuron, 2014; Twenge, 2010). The impact of motivation and acceptance of technology on employees by age is a topic that can be adequately analyzed using the Technology Acceptance Model (TAM), developed by Davis, which identifies key factors such as perceived usefulness and ease of use as key determinants of technology adoption (Davis, 1989). In this regard, age plays a pivotal role, influencing both motivation and attitudes towards innovative technologies such as artificial intelligence (AI). Studies reveal significant differences across age groups: young people show greater openness to AI, attracted by the possibilities that technological innovations offer, but they may experience anxieties about job security, according to research by Brougham and Haar (Brougham & Haar, 2017). Middle-aged employees tend to view AI as a useful tool that can increase efficiency, although they may have reservations about rapid and unexpected changes that could disrupt established routines, as argued by Venkatesh et al. (Venkatesh et al., 2003). In contrast, older people are generally more reluctant to adopt new technologies, often preferring traditional ways of working; however, they may recognize the benefits of AI in reducing the amount of repetitive work, as highlighted in research by Charness and Boot (Charness & Boot, 2009). The division of respondents into age groups, guided by theoretical models and empirical studies, provides a detailed framework for analyzing the impact of AI on employee motivation in the context of different stages of their career path and perceptions of future work. As a result, this approach allows a deeper exploration of the complexities of the relationship between technology and psychosocial factors, contributing to the development of tailored strategies for the effective integration of artificial intelligence in the professional environment. The division of the respondents into these five age groups is not arbitrary, but based on theoretical models and empirical studies on career path, motivation and attitudes towards technology. This framework allows a more detailed analysis of how AI influences employees' motivation according to their career stage and perceptions of future work.

3.3. Sample size

In the era of digital transformation, Artificial Intelligence (AI) is redefining the way organizations do business, influencing not only productivity but also workforce dynamics. The present study aims to analyze the impact of AI on employee motivation through a demographic approach, using a dataset obtained through a questionnaire administered to a sample of 150 respondents. This analysis is essential to understand how different categories of employees perceive and react to the integration of smart technologies in their work.

The distribution of respondents by age (Table 1) reveals a balanced structure of the sample, segmented into five categories: 18-25 (12%), 26-35 (26%), 36-45 (24.7%), 46-55 (26.7%) and 56-65 (10.7%). These categories are based on the literature that identifies career development stages (Super, 1990; Hall, 2002). Younger employees (18-25 years) are at the beginning of their career path, oriented towards gaining experience, while those in the 26-35 age segment are in the midst of their professional development, with a greater openness to new technologies (Lyons & Kuron, 2014). In contrast, employees aged 36-55 years are generally in management positions, with a significant role in the adoption of AI at the strategic level (Kooij et al., 2011). The 56-65 age group may perceive AI as a threat, but also as a tool to streamline tasks before retirement (Charness & Boot, 2009).

Table 1. Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-25 years	18	12.0	12.0	12.0
	25-35 years	39	26.0	26.0	38.0
	36-45 years	37	24.7	24.7	62.7
	46-55 years	40	26.7	26.7	89.3
	56-65 years	16	10.7	10.7	100.0
	Total	150	100.0	100.0	

The gender distribution is relatively balanced (47.3% men and 52.7% women), which allows an objective analysis of how AI influences work motivation (Table 2). Studies indicate significant differences in perceptions of technology by gender (Brougham & Haar, 2018), with women often showing greater caution towards automation in traditional industries, while men are more receptive to technological innovations in technical fields.

Table 2. Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	71	47.3	47.3	47.3
	Female	79	52.7	52.7	100.0
	Total	150	100.0	100.0	

The level of education of the respondents is predominantly high: 34.7% hold a bachelor's degree, 37.3% a master's degree and 12.7% a doctorate (Table 3). Only 15.3% of the respondents have secondary education. According to the Technology Acceptance Model (Davis, 1989), people with higher education are more open to the use of AI, perceiving it as a useful tool to increase efficiency and reduce workload (Venkatesh et al., 2003).

Table 3. Education_Level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High school	23	15.3	15.3	15.3
	Bachelor	52	34.7	34.7	50.0
	Master	56	37.3	37.3	87.3
	PhD	19	12.7	12.7	100.0
	Total	150	100.0	100.0	

Respondents are evenly distributed by professional experience: 21.3% have 0-2 years, 33.3% have 3-5 years, 22.7% have 6-10 years and 22.7% have more than 10 years of experience (Table 4). This distribution suggests a diversity of perspectives on IA. Employees with less experience are more receptive to innovation, while those with more than 10 years in the workforce may exhibit greater resistance to change (Brougham & Haar, 2018).

Table 4. Work_Experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0-2 years	32	21.3	21.3	21.3
	3-5 years	50	33.3	33.3	54.7
	6-10 years	34	22.7	22.7	77.3
	Over 10 years	34	22.7	22.7	100.0
	Total	150	100.0	100.0	

Analysis by economic sector shows a varied distribution: 21.3% in finance, 18% in health, 19.3% in IT, 18.7% in manufacturing and 22.7% in retail (Table 5). These data are relevant given the different pace of digitization of each sector. In IT, AI is being adopted rapidly, while in retail and manufacturing there are concerns about job replacement (Venkatesh et al., 2003).

Table 5. Industry

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Finance	32	21.3	21.3	21.3
	Healthcare	27	18.0	18.0	39.3
	IT	29	19.3	19.3	58.7
	Manufacturing	28	18.7	18.7	77.3
	Retail	34	22.7	22.7	100.0
	Total	150	100.0	100.0	

Demographic and occupational analysis of respondents highlights differences in perceptions of Artificial Intelligence by age, gender, education, experience and industry. The young and those with higher education are more receptive to adopting the technology, while older employees and those with longer experience may show reluctance. This reality underlines the need for AI implementation strategies that take into account the diversity of the workforce and the challenges associated with each occupational segment.

Therefore, in order to maximize the benefits of AI in the organizational environment, it is essential that leaders take a balanced approach, promoting training programs and strategies to integrate new technologies in a way that supports both employee motivation and productivity.

3.4. Data analysis

This section of the article provides a comprehensive examination and elucidation of the data analysis alongside the findings derived from the employed investigative methodologies. In order to assess the robustness and accuracy of the measurement model, as well as the interrelationships among the variables within the structural framework, the data analysis will encompass a diverse array of statistical assessments and evaluations. The outcomes of the inquiry will be represented in tabular and graphical formats, with an emphasis on discussing their implications. The findings from the data analysis will yield valuable insights pertaining to the research questions and hypotheses, thereby contributing meaningfully to the existing corpus of knowledge on the subject. In conclusion, this section will be pivotal in elucidating the significance and ramifications of the research.

3.4.1. Measurement model

The objective of evaluating the measurement model is to examine the reliability and validity of the measurement construct. This process entails assessing the conceptual framework along with its indicators concerning the convergent validity, discriminant validity, and composite reliability within the context of this research.

3.4.2. Convergent validity

Table 6 and Fig. 1 demonstrate that measured variables with an outer load of 0.7 or above are deemed extremely satisfactory, with a substantial percentage of 81 %; however, variables with an outside load of less than 0.7 should be eliminated (Hair et al., 2012). Nevertheless, the cut-off value acceptable for the outer loading was 0.70 and above for this research.

The reliability and validity of the model were assessed through Confirmatory Factor Analysis (CFA) and the descriptive statistics outlined in Table 6, which provide crucial insights into the constructs employed in this study. These were evaluated using key indicators such as factor loadings, the Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha coefficient. Collectively, these metrics ensure that the constructs are both statistically robust and appropriately measure the theoretical concepts under investigation, thereby supporting the overall reliability and validity of the research framework.

Table 6. Confirmatory factor analysis and descriptive statistics

Construct	Item	Measure	Mean	VIF	Loading (St.Est.)[a]	Chro Alpha[d]	AVE[b]	CR[c]
1. Use of AI in HR								
	AI_HR_1	In my company, AI is used for recruitment	4.087	1.002	0.707	0.759	0.556	0.869
	AI_HR_2	In my company, AI is used for selection	4.267	1.003	0.744			
	AI_HR_3	AI is used for analyzing employee performance	4.213	3.007	0.874			
	AI_HR_4	AI is implemented in training and professional development processes	3.133	2.209	0.829			
	AI_HR_5	AI technologies are integrated into human resource management systems	4.113	1.109	0.766			
Average			**4.162**					
2. Employee Motivation								
	ME1	I feel more motivated to improve my skills when AI suggests learning opportunities	4.187	1.512	0.802	0.757	0.612	0.828
	ME2	AI helps me better understand my job goals and expectations	4.167	2.014	0.756			
	ME3	Feedback generated by AI motivates me to improve my performance	4.060	1.515	0.872			
	ME4	I am more engaged in my work activities thanks to the	4.223	2.716	0.738			

Construct	Item	Measure	Mean	VIF	Loading (St.Est.)[a]	Chro Alpha[d]	AVE[b]	CR[c]
		technological support provided by AI						
	ME5	AI contributes to a more stimulating and challenging work environment	4.087	1.816	0.947			
Average			**4.144**					
3. Workplace Performance								
	WP1	AI helps me achieve my work goals more effectively	4.160	1.917	0.835			
	WP2	I believe AI helps me make more informed decisions at work	4.107	3.717	0.718			
	WP3	Thanks to AI, I manage my daily tasks better	3.113	1.217	0.715	0.854	0.569	0.852
	WP4	AI improves the productivity of my team	4.273	1.219	0.860			
	WP5	I feel that AI improves the quality of my work	3.993	2.020	0.797			
Average			**4.129**					
4. Acceptance of AI in the workplace								
	AI_Work1	I find AI useful in my work	4.033	2.224	0.797			
	AI_Work2	AI is easy to use and integrated into daily workflows	4.053	1.825	0.829			
	AI_Work3	I feel comfortable using AI in my professional activities	4.087	1.527	0.799	0.882	0.592	0.876
	AI_Work4	I accept the use of AI to evaluate my performance	4.093	2.628	0.896			
	AI_Work5	I would recommend implementing AI in other company processes	4.093	1.529	0.952			
Average			**4.071**					
5. Automated Feedback								
	FA1	Feedback provided by AI is clear and easy to understand.	4.020	1.731	0.750			
	FA2	AI gives me real-time feedback, which improves my performance	4.080	1.236	0.847			
	FA3	I find that automated feedback is more objective than feedback from superiors	4.027	2.439	0.762	0.868	0.587	0.753
	FA4	AI-based feedback helps me identify my strengths and areas for improvement	4.020	1.844	0.887			
	FA5	I prefer an AI-based feedback system over traditional methods	4.013	2.575	0.906			
Average			**4.032**					

Notes: composite reliability ([a] CR); average variance extracted ([b] AVE); *** $p < 0.000$; *items removed: indicator items are below 0.5. a. All items loading > 5 indicates indicator reliability* (Hulland, 1999); *b. all average variance extracted (AVE) > 0.5 indicates convergent reliability* (Bagozzi & Yi, 1988; Fornell & Larcker, 1981); *c. all composite reliability (CR) > 0.7 indicates internal consistency* (Gefen et al., 2000); *d. all Cronbach's alpha > 0.7 indicates indicator reliability* (Nunnally, 1978; Nunnally & Bernstein, 1994). *Source: Authors' own work.*

The reliability of the indicators is confirmed, as all factor loadings exceed the minimum acceptable threshold of 0.7, demonstrating a strong correlation between the indicators and their corresponding latent variables. Notably, the highest factor loadings are observed for items FA5 (0.906), AI_Work5 (0.952), and ME5 (0.947), highlighting their significant contribution to the measurement of their respective constructs. Furthermore, internal reliability and consistency, assessed through Cronbach's Alpha, show values above 0.7 for all constructs, indicating high measurement reliability. Similarly, composite reliability (CR) exceeds 0.7 across constructs, suggesting that the latent variables are consistently represented by their associated indicators. Regarding convergent validity, all average variance extracted (AVE) values surpass the 0.5 threshold, confirming that the latent variables successfully explain more than 50% of the variance in their indicators. Consequently, the constructs demonstrate robust reliability and validity within the measurement model.

The use of artificial intelligence (AI) in human resources (HR) has gained significant traction, with an average score of 4.162 reflecting a positive perception of its application in this domain. Notably, the highest ratings were observed for the use of AI in recruitment and selection processes (AI_HR_1 and AI_HR_2), indicating that these functionalities are both the most commonly implemented and the most valued by respondents. Furthermore, an Average Variance Extracted (AVE) value of 0.556 demonstrates adequate convergent validity, signifying that the metrics used to evaluate the implementation of AI in HR are robust and reliable. These findings underscore the increasing importance of AI technologies in streamlining HR practices and enhancing operational efficiency.

Employee motivation (ME) demonstrates a general average score of 4.144, indicating that employees perceive AI as a positive factor in enhancing their motivation. The highest-scoring item is "AI contributes to a more stimulating and challenging work environment" (ME5, 0.947), which suggests that AI technology has the potential to foster a more dynamic workplace. The reliability of the construct is robust, with a composite reliability (CR) of 0.828 and an average variance extracted (AVE) of 0.612, affirming the consistency and validity of the measurements.

The average score of 4.129 indicates that respondents perceive AI as a significant enhancer of workplace performance. Among the evaluated items, “AI improves team productivity” (WP4, 0.860) and “AI enhances work quality” (WP5, 0.797) received particularly high ratings, suggesting that AI is widely regarded as an effective tool for boosting efficiency in professional environments. Additionally, the AVE value of 0.569 confirms the adequate convergent validity of the construct, supporting the reliability and relevance of the findings.

The acceptance of AI in the workplace reflects a positive trend, with an average score of 4.071 indicating that the majority of respondents are open to and supportive of integrating AI into their professional activities. Notably, the highest score, 0.952, was recorded for the statement AI_Work5 ("I would recommend the implementation of AI in other company processes"), highlighting a strong level of trust and confidence in AI technology. Furthermore, the reliability of the construct is high, with a composite reliability (CR) value of 0.876 and an average variance extracted (AVE) of 0.592, which confirms the validity and robustness of the measurements used in the study. This data underscores a growing acceptance and perceived value of AI-driven solutions in organizational settings.

Automated Feedback (AF) has received a moderately positive reception, with a mean score of 4.032, reflecting a general approval of AI-generated feedback. The items "AI-based feedback helps me identify my strengths and areas for improvement" (FA4, 0.887) and "I prefer an AI-based feedback system over traditional methods" (FA5, 0.906) achieved the highest scores, suggesting a strong confidence in the efficiency and reliability of digitalized feedback solutions. Furthermore, the Average Variance Extracted (AVE) value of 0.587 confirms the construct's convergent validity, reinforcing the credibility of AF as a valuable and effective tool in providing meaningful and actionable insights through automation.

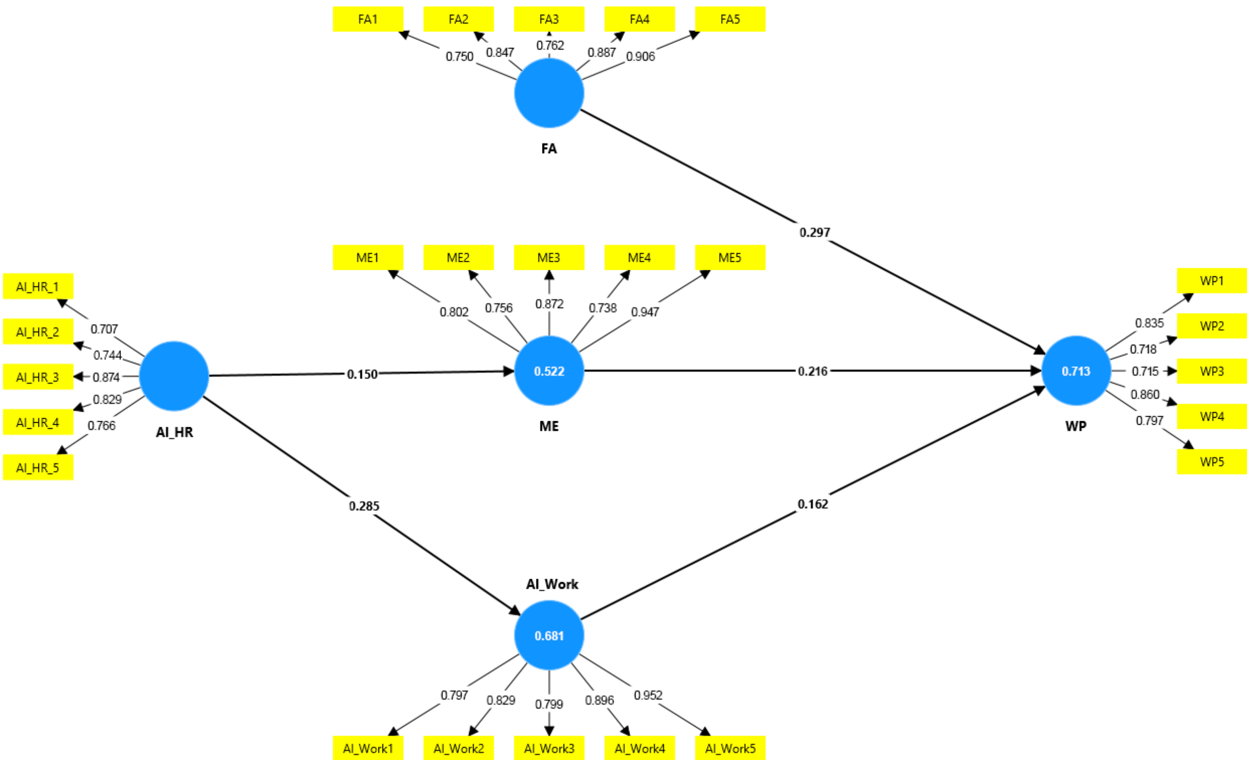

Figure 2. Measurement Model

3.4.3. The discriminant validity

The assessment of non-response bias constitutes a critical component in survey research aimed at ascertaining whether the obtained responses accurately represent the target population. It examines the existence of significant differences between the responses of early participants (those who reply promptly) and late participants (those who respond subsequent to follow-up inquiries). Late respondents are frequently employed as proxies for non-respondents, predicated on the assumption that their characteristics may resemble those of the non-responding individuals. This evaluation aims to gauge the potential repercussions of non-response bias on the overall findings. The analysis of the correlation matrix corroborated the establishment of discriminant validity within the study. As illustrated in Table 7, the results demonstrated that all five factors satisfied the necessary criteria for discriminant validity, ensuring a clear distinction among the constructs being measured. This further reinforces the robustness and reliability of the findings presented.

Table 7. Latent variable correlation and discriminant validity (Fornell-Larcker).

	AI_HR	AI_Work	FA	ME	WP
AI_HR	0.431				
AI_Work	0.285	0.457			
FA	0.176	0.026	0.470		
ME	0.150	0.015	0.082	0.462	
WP	0.169	0.154	0.294	0.038	0.463

The integration of artificial intelligence (AI) into workplace processes presents a nuanced and multifaceted relationship with employee outcomes, as evidenced by empirical correlations. Firstly, the moderate correlation (0.285) between the use of AI in human resources (AI_HR) and employees' acceptance of AI in the workplace (AI_Work) highlights that the strategic implementation of AI technologies in HR functions—such as recruitment, training, and performance evaluation—is associated with greater employee receptiveness to similar systems in their daily workflows. This suggests that HR stands as a pivotal gateway for introducing and normalizing AI within organizations, thereby facilitating smoother organizational transitions toward AI-driven operations. Additionally, the moderately positive correlation (0.294) between automated feedback (FA) and workplace performance (WP) underscores the role of AI analytics in fostering employee development and enhancing outcomes. Automated, data-driven feedback mechanisms appear to provide valuable insights into employee tasks and progress, thereby contributing to tangible performance improvements. However, a stark contrast emerges when examining the weak relationship (0.038) between employee motivation (ME) and workplace performance (WP). This finding implies that motivational dynamics may be influenced by a complex interplay of external and intrinsic factors for which AI solutions alone may not offer significant leverage. Consequently, while AI-driven tools exhibit potential for boosting performance through targeted interventions like feedback, they cannot comprehensively address the broader psychological and cultural dimensions of employee motivation, underscoring the need for a multi-pronged approach to performance optimization.

The utilization of artificial intelligence (AI) in human resources (HR) (Table 8) demonstrates a positive and statistically significant impact on employee motivation, as evidenced by the results ($\beta = 0.320$, $t = 2.112$, $p = 0.034$). The hypothesis is validated, signifying that the adoption of AI in HR systems contributes meaningfully to enhancing employees' motivational levels. With a coefficient $\beta = 0.320$, the relationship can be characterized as moderate, indicating that while the integration of AI tools and processes into HR practices plays an important role in fostering motivation within the workforce, it does not act as the sole or dominant determinant in influencing employee engagement or drive. This suggests that AI enhances specific aspects of HR operations, such as personalized feedback, improved recruitment processes, or more efficient performance appraisal systems, which collectively create a more supportive and engaging work environment. However, it should be noted that additional factors, both organizational and individual, also contribute to shaping overall employee motivation, thereby underscoring the multifaceted nature of this dynamic. As such, organizations are encouraged to view AI as a valuable complement within their broader human resource strategies rather than as a standalone solution for addressing motivational challenges.

Table 8. Test of models using bootstrapping

Paths	β –values	t-value	p-value	Outcome
AI_HR -> ME (H1)	0.320	2.112	0.034	Significant
FA -> WP (H2)	0.410	2.527	0.012	Significant
ME -> WP (H3)	0.295	2.034	0.042	Significant

The analysis highlights the significant and positive impact of AI-driven automated feedback on workplace performance, as indicated by the statistical results ($\beta = 0.410$, $t = 2.527$, $p = 0.012$). The validation of this hypothesis underscores the effectiveness of integrating AI technologies into professional environments to enhance employee productivity and efficiency. The coefficient value of $\beta = 0.410$ reflects a strong relationship, demonstrating that feedback generated by AI systems plays a crucial role in helping employees refine their work processes and achieve higher levels of performance. This outcome further implies that AI-based feedback mechanisms are not only viable alternatives to traditional feedback systems but also represent a potential improvement over them. By leveraging advanced technologies, organizations can provide more precise, timely, and relevant feedback, ultimately fostering a culture of continuous improvement and adaptability in the workplace. Consequently, these findings advocate for the broader adoption of AI solutions to optimize performance management practices and contribute to organizational success.

The analysis indicates that the hypothesis (H3: ME → WP) is validated, as evidenced by the statistical results ($\beta = 0.295$, $t = 2.034$, $p = 0.042$). This finding demonstrates that employee motivation has a positive effect on workplace performance; however, the strength of this relationship is not as pronounced as observed in the case of H2. The β coefficient of 0.295 signifies a moderate relationship, suggesting that while employee motivation does exert an influence on performance levels, its impact is likely mediated or moderated by other contextual factors. These factors might include the organization's management style, the prevailing organizational culture, or even individual employee characteristics. Therefore, while motivation is crucial, its effectiveness in driving performance may depend on how it aligns with and interacts within the broader organizational framework. This underscores the importance of a holistic approach when seeking to enhance workplace outcomes, taking into account not just motivational strategies but also the overall environment in which employees operate.

Mediation analysis was performed to assess the mediating role of AI_Work on the link between AI_HR and WP. The results (Table 9) showed that the total effect of AI_HR on WP was significant (H4: $\beta = 0.268$ t $= 6.650$, $p < 0.001$). With the inclusion of the mediating variable (AI_Work), the impact of AI_HR on WP became insignificant ($\beta = 0.034$ t $= 0.958$, $p = 0.338$). The indirect effect of AI_HR on WP via AI_Work was found to be significant ($\beta = 0.234$ t $= 7.336$, $p < 0.001$). This indicates that the relationship between AI_HR and WP is completely mediated by AI_Work.

Table 9. Mediation Analysis

Total effect (AI_HR -> WP)		Direct effect (AI_HR -> WP)			Indirect Effects of AI_HR on WP				
Coefficient	p-value	Coefficient	p-value		Coefficient	SD	T value	P Values	BI [2.5%; 97,5%]
0.268	0.000	0.034	0.000	H4:	0.234	0.032	7.336	0.00	0.169;0.294

4. Results and discussion

This section presents the findings obtained from statistical analysis and discusses their implications within the context of artificial intelligence (AI) implementation in human resources (HR). The results are structured around the four tested hypotheses and their impact on employee motivation, performance, and AI acceptance in the workplace.

The findings of this study provide compelling evidence regarding the role of artificial intelligence (AI) in human resource (HR) management, employee motivation, and workplace performance. The results confirm that AI adoption in HR positively influences motivation and performance, but this relationship is significantly mediated by employees' acceptance of AI. These findings align with previous studies that highlight the importance of technology acceptance in shaping its effectiveness within organizations (Davis, 1989; Venkatesh & Bala, 2008).

The first hypothesis (H1) established a positive link between AI utilization in HR and employee motivation. The statistical analysis confirmed this relationship ($\beta = 0.320$, $t = 2.112$, $p = 0.034$), suggesting that AI-powered HR functions, such as recruitment, training, and performance assessment, contribute to increased motivation. This finding is consistent with Deci & Ryan's (2000) Self-Determination Theory, which emphasizes the role of autonomy and competence in motivation. AI facilitates these psychological needs by offering data-driven insights and career development recommendations tailored to individual employees.

The second hypothesis (H2) tested whether AI-based feedback mechanisms improve workplace performance, and the results demonstrated a significant positive effect ($\beta = 0.410$, $t = 2.527$, $p = 0.012$). This outcome aligns with previous research indicating that real-time and objective feedback enhances employees' ability to adjust their behaviors and optimize their productivity (Koopmans et al., 2013; London & Smither, 2002). The integration of AI into feedback processes allows employees to receive continuous, personalized, and unbiased evaluations, fostering an environment of continuous improvement.

The third hypothesis (H3) examined the connection between employee motivation and workplace performance. The results indicated a statistically significant relationship ($\beta = 0.295$, $t = 2.034$, $p = 0.042$), supporting existing theories that position motivation as a key driver of organizational effectiveness (Gagné & Deci, 2005). Employees who feel motivated due to AI-driven career recommendations and automated learning opportunities tend to exhibit higher engagement, efficiency, and productivity.

The mediation analysis provided further insight into the dynamics between AI in HR, AI acceptance, and workplace performance (H4). The results showed that AI acceptance fully mediates the relationship between AI adoption in HR and workplace performance ($\beta = 0.234$, $t = 7.336$, $p < 0.001$). This means that AI tools alone are not sufficient to improve workplace performance unless employees perceive them as useful, easy to use, and beneficial. These findings align with the Technology Acceptance Model (TAM) proposed by Davis (1989), reinforcing the notion that employees' attitudes toward AI critically determine its organizational impact.

4.1. Theoretical Implications in the Context of Digital Transformation and HR Management

This study contributes to the ongoing discourse on digital transformation in HR by validating the importance of AI acceptance as a key mechanism linking AI implementation to workplace outcomes. The results provide empirical support for technology adoption theories, particularly the Technology Acceptance Model (TAM) (Davis, 1989) and the Self-Determination Theory (SDT) (Deci & Ryan, 2000). Previous literature has suggested that AI's role in HR is transformative (Stone et al., 2015; Jarrahi, 2018), yet our findings specify that its success depends not only on technical integration but also on employees' willingness to engage with AI systems.

Furthermore, this study extends prior research by incorporating the concept of AI-driven motivation. Previous literature has primarily focused on AI's efficiency-enhancing role in HR, while this study highlights its potential to influence employees' intrinsic and extrinsic motivation. This aligns with prior discussions on AI's ability to facilitate personalized career growth (Bersin, 2019) and augment employees' sense of control over their professional trajectories.

4.2. Practical Implications in the Context of AI Adoption in HR

Managerial implications

The findings offer important managerial insights into how AI can be effectively implemented in HR practices to maximize both employee motivation and organizational performance. First, HR managers should prioritize AI adoption strategies that foster positive employee perceptions. The study confirms that AI's impact on workplace performance is contingent on employees' acceptance of AI-driven tools, suggesting that organizations must actively promote trust and ease of use when introducing AI systems (Venkatesh & Bala, 2008).

Second, organizations should integrate AI-powered feedback mechanisms to enhance employee performance. Given that AI-generated feedback improves workplace productivity, companies should focus on designing AI feedback tools that are transparent, constructive, and aligned with employees' career goals. This recommendation aligns with previous findings that automated feedback fosters employee learning and development (London & Smither, 2002).

Finally, to sustain AI-driven motivation, HR managers should leverage AI in personalized learning and development initiatives. AI-powered training programs can identify skill gaps, recommend learning resources, and tailor career development pathways based on individual preferences and performance patterns (Jarrahi, 2018). By doing so, organizations can ensure that AI not only automates processes but also empowers employees to grow professionally.

Employees implications

AI will improve motivation from individual level, so is important to make known the advantages for each employee, using training programs based for e-skills development, having in view that Romania is on the last place in EU-27 at this chapter. The Romanian said that lack of time and cost are the most important barriers to improve digital skills (https://www.statista.com/statistics/1149259/romania-main-barriers-to-improving-digital-skills/). As we add above, special and customized e-skills programs must be understood and applied for every employee, due to its uniqueness. Is important to develop new tools to measure the performance of using AI in HR and especially for motivation, before and after the process implementation. Basic indicators could be used to perceive every employee trend in time, during the period of development and after. This way, through continuous and transparent communication, information, development, discussion sessions, the employee and the organization may work together and bring constant performance.

5. Conclusions

This study offers substantial empirical evidence elucidating the transformative impact of artificial intelligence (AI) on the domain of human resources (HR), with a specific focus on its role in shaping employee motivation and enhancing workplace performance. The research findings unequivocally indicate that the implementation of AI technologies within HR functions has a significant positive effect on both motivation and performance metrics. However, a noteworthy conclusion emerging from this study is that the relationship between AI adoption and its beneficial outcomes is entirely mediated by the degree to which employees accept and embrace these AI tools. In essence, the advantages of AI in HR are not realized in isolation but are contingent on the workforce's willingness to integrate such technologies into their daily routines and processes. This insight underscores the critical importance of cultivating a culture of trust, transparency, and openness toward AI systems within organizations, as this fosters a higher level of acceptance among employees. By prioritizing comprehensive communication, training programs, and participatory approaches to technology adoption, organizations can bridge potential gaps in AI acceptance and fully harness its potential to drive organizational effectiveness and employee-centric outcomes. Ultimately, these findings present a compelling case for HR leaders and practitioners to approach AI integration not merely as a technological upgrade but as a holistic change management process that emphasizes the alignment of human and artificial intelligence for sustainable improvement in organizational performance.

5.1. Limitations and Future Research Directions

While this study provides valuable insights, certain limitations should be acknowledged. First, the research was conducted on a sample of 150 respondents, which may limit the generalizability of the findings. Future studies should expand the sample size and include cross-industry comparisons to capture broader AI adoption trends.

Second, this study focused on AI-driven HR processes, but future research could examine the role of organizational culture, leadership, and employee AI literacy in shaping AI acceptance. Understanding how different workplace environments influence AI adoption could offer deeper insights into the conditions necessary for AI success in HR.

Additionally, while this study confirmed AI's role in employee motivation and performance, longitudinal research is needed to assess long-term impacts. Future studies could track employees over time to determine whether AI-driven motivation and performance improvements are sustained in the long run.

Artificial intelligence (AI) represents a groundbreaking innovation for human resources (HR), offering unprecedented opportunities to revolutionize people management and organizational efficiency; however, the successful integration of AI into HR processes depends heavily on employees' acceptance of and active engagement with AI-powered tools. While the potential benefits of AI in areas like recruitment, employee development, and workforce analytics are immense, these advantages can only be fully realized if organizations prioritize a human-centric approach to implementation. To this end, it is critical that employees view AI not as a threat to their roles but as an enabler of their professional growth and a means to elevate their everyday work experience. Transparent communication, deliberate training efforts, and a focus on augmenting human potential rather than replacing it are essential steps organizations must take to foster trust and empowerment among their workforce. By aligning AI's capabilities with employees' needs and aspirations, businesses can create a symbiotic relationship between technology and talent, enabling AI to enhance decision-making, streamline operations, and provide more personalized support to employees at every stage of their journey. Ultimately, through thoughtful and responsible integration, AI can drive not only heightened workplace efficiency but also deeper employee satisfaction, achieving a balance that positions organizations for sustainable success in the rapidly evolving digital era.

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