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Unraveling the Reshaping of Human Resource Management Function: The Mediating Role of Artificial Intelligence

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ABSTRACT

The dynamic nature of the modern work environment is characterized by increasing complexity, diversity, and adaptability beyond traditional workplaces. This shift is predominantly driven by advanced technologies transforming human resource management functions within organizations. Integrating artificial intelligence AI into HR practices represents a significant development, enhancing organizational capabilities while streamlining manual processes. This study aims to analyse the transformative impact of AI on HR management, evaluate its positive and negative impact on HR practices, and identify the associated challenges and opportunities related to the adoption of AI in HRM. A quantitative research methodology was employed, utilizing a survey instrument based on a 5.0 Likert scale. The sample consisted of 103 employees from various departments and levels within a selected organization in Durban, out of a targeted population of 500 employees, selected through simple random sampling. The results indicate that AI supports HRM professionals in executing tasks more efficiently and facilitates data analysis and process optimization. Additionally, the findings suggest that AI contributes to streamlining HR processes and has a positive impact on work-life balance, demonstrating that automation can improve both operational efficiency and employee well-being. However, the study also identifies potential challenges associated with AI adoption, including concerns related to algorithmic bias, data privacy, transparency, and employee apprehensions. Despite these obstacles, AI has the potential to enhance HRM practices and support effective talent management strategies significantly. It is recommended that organizations focus on increasing AI literacy among employees and involve staff in the development of AI policies to promote acceptance and reduce resistance to technological advancements.

1. INTRODUCTION

The evolving work ecosystem is becoming increasingly complex, diverse, and adaptable compared to traditional work environments. This transformation is driven by advanced technologies that are reshaping how we work. One of the most significant technologies of the 21st century is artificial intelligence (AI) (Wamba et al., 2021). AI is generally defined as a system capable of understanding and mimicking human intelligence, particularly in repetitive, rule-based tasks while providing precision, speed, and cost efficiencies (Kondapaka et al., 2023). Duan et al. (2019) note that there is no universally accepted definition of AI; it is typically characterized as the ability of a machine to learn from experience, adapt to new inputs, and execute tasks traditionally performed by humans. Various AI technologies exist, including machine learning (ML), deep learning (DL), and more commonly utilized generative AI (Zhuhadar and Lytras, 2023).

Founded on the ongoing discussion, the rapid integration of artificial intelligence into human resource management has significantly influenced organizational operations, presenting both opportunities and challenges. This study aims to provide a thorough analysis of AI's impact on HR practices, offering practical insights into the benefits and potential drawbacks of AI applications in HR functions. It also includes recommendations to assist HR professionals and organizations in effectively managing this technological transition. For example, AI-driven tools enhance recruitment processes by automating candidate screening, reducing bias, and alleviating managerial workload (Chen, 2023). Additionally, AI supports personalized training programs and facilitates predictive workforce planning (Bhatt & Muduli, 2022). However,

implementing AI also has implications for HR practitioners and employee well-being, which may lead to shifts in performance expectations and potential resistance to change (Stamate et al., 2021). Despite the growing body of literature on AI and HRM, several gaps remain that this study aims to address. Most existing research predominantly concentrates on specific HRM functions such as recruitment and selection, with less emphasis on areas like compensation, workplace safety, and employee negligence (Ahmić, 2023). Furthermore, studies examine the application of AI in résumé screening (Bongard, 2019; Chen, 2023), but its effects on broader aspects of challenges associated with the implementation of AI in HRM are limited. In addition, few studies provide nuanced, comprehensive analyses of the opportunities offered by AI in HRM (Ekuma,2024). This research aims to bridge that gap by integrating both the positive and negative impacts of AI applications in HRM functions/operations.

2. LITERATURE REVIEW

Benabou, Touhami and Demraoui (2024) suggest that the integration of artificial intelligence (AI) into human resource management (HRM) practices marks a significant advancement in the workplace, enhancing organizational capabilities while reducing the necessity for human involvement. This study aims to explore the transformative effects of AI on HRM, assess its impacts on HR practices, and analyse the challenges associated with its implementation in human resource management, as well as the opportunities that AI presents within this field.

- H^1 Artificial intelligence hurts the HRM function
- H^2 Artificial intelligence has a positive impact on the HRM function

Artificial Intelligence (AI) is significantly impacting recruitment and selection processes in organizations. AI technologies like natural language processing, machine vision, and automation are enhancing efficiency, reducing costs, and improving accuracy in hiring (Hemalatha et al., 2021). AI-powered tools are being rapidly adopted by companies of various sizes to manage the entire hiring process, revolutionizing traditional recruitment methods (Jha et al., 2019). Furthermore, AI's ability to analyze large volumes of data facilitates more informed and objective decision-making, thereby supporting diversity and inclusivity in the hiring process (Tripathi, 2024). Founded on ongoing deliberations regarding the impact of artificial intelligence on human resource management functions, Bughin et al. (2017) indicate that the implementation of AI in recruitment processes can reduce costs by up to 30%, while simultaneously enhancing the quality of candidate selection. However, it is important to note, as highlighted by Dastin (2018), that AI's dependence on historical data can perpetuate existing biases if not monitored effectively. For instance, Amazon's AI recruitment tool previously downgraded resumes that included female-associated terms due to biased training data. Additionally, AI facilitates predictive analytics to identify high-potential candidates, thereby enhancing talent acquisition strategies. Bersin (2019) points out that AI-driven training platforms can increase employee productivity by 14% through targeted upskilling. Furthermore, the use of virtual reality (VR) and AI simulations creates immersive training environments, particularly beneficial for technical roles. It is essential, however, to heed the caution raised by Sparrow (2020), who suggests that excessive reliance on AI could lead to depersonalization of learning experiences, diminishing the emotional impact of human mentorship.

Chui et al. (2018) assert that AI-driven performance management systems can improve appraisal accuracy by 20% compared to traditional methods. Continuous feedback platforms powered by AI also contribute to a culture of ongoing improvement, moving away from outdated annual review processes. Nonetheless, Tambe et al. (2019) argue that employees may feel excessively monitored if AI tools track performance too intrusively, potentially raising privacy concerns. Manyika et al. (2017) emphasize that AI can significantly enhance the efficiency of workforce planning, achieving improvements of up to 25% and enabling data-driven decision-making. People analytics platforms, such as Visier, provide correlations between employee data and business outcomes, yielding valuable insights into productivity drivers. However, Zuboff (2019) warns that extensive data collection practices can undermine trust if employees perceive these efforts as exploitative.

The implementation of artificial intelligence (AI) in human resource management (HRM) presents several challenges that organizations must navigate. Persistent concerns regarding organizational resistance, ethical considerations, and technological limitations serve as significant obstacles (Ghezelseflou, 2023). Ethical issues include bias, discrimination, privacy, and the need for transparency therefore, legal challenges arise from the necessity to comply with data protection and anti-discrimination regulations (Du, 2024). The complex nature of HR phenomena and the limitation of small datasets further restrict the application of AI technologies (Tambe et al., 2019). Furthermore, there is a growing demand for AI specialists and customized solutions that align with institutional standards (Salman, 2024). To effectively address these challenges, organizations should prioritize causal reasoning, the use of randomization and experiments, and leverage employee contributions (Tambe et al., 2019). Despite these barriers, the integration of AI in HRM holds the potential to significantly improve efficiency, enhance decision-making, and elevate the

employee experience (Ghezelseflou, 2023). Responsible management practices must be implemented to ensure the successful integration of AI into HRM processes.

Conceptual Linkages of Variables

This literature review examines the integration of artificial intelligence (AI) into human resource management (HRM) processes, analyzing the conceptual linkages whereby AI functions as the independent variable influencing multiple HRM functions, which serve as the dependent variables.

Independent Variable: Artificial Intelligence (AI)

Artificial Intelligence (AI) comprises advanced computational methodologies including machine learning (ML), deep learning (DL), natural language processing (NLP), machine vision, automation systems, and generative AI models. These methodologies are instrumental in revolutionizing Human Resource Management (HRM) through the automation of administrative processes, enhancement of decision-making accuracy, and optimization of operational efficiency. Nonetheless, their deployment presents challenges related to algorithmic bias, data privacy, and ethical considerations.

Dependent Variables: HRM Functions

- Recruitment and Selection**:** AI-driven tools automate candidate screening, reduce bias, and improve hiring efficiency (e.g., cost reduction by up to 30% as per Bughin et al., 2017). However, reliance on historical data can perpetuate biases if not managed (Dastin, 2018).
- Training and Development: AI supports personalized training programs and immersive learning environments (e.g., VR simulations), increasing productivity by 14% (Bersin, 2019). However, it risks depersonalizing learning experiences (Sparrow, 2020).
- Performance Management: AI-powered systems enhance appraisal accuracy by 20% and enable continuous feedback (Chui et al., 2018). Yet, intrusive monitoring may raise privacy concerns (Tambe et al., 2019).
- Workforce Planning: AI improves efficiency by 25% through predictive analytics and people analytics platforms (Manyika et al., 2017). However, extensive data collection can erode trust (Zuboff, 2019).
- Other HRM functions, such as compensation, workplace safety, and employee negligence, are underexplored but potentially impacted by AI's capabilities and limitations.

Mediating Variables: Opportunities and Challenges

- Opportunities**:** AI enhances efficiency, reduces costs, supports diversity, and enables data-driven decision-making across HRM functions. For example, AI improves candidate selection quality and supports inclusivity (Tripathi, 2024).
- Challenges: These include ethical issues (bias, discrimination, privacy), organizational resistance, technological limitations (e.g., small datasets), and legal compliance (Du, 2024; Tambe et al., 2019). These challenges mediate the extent to which AI positively or negatively impacts HRM.

Moderating Variables: Organizational and Employee Factors

- Organizational Resistance: Resistance to AI adoption due to cultural or structural factors can hinder its effectiveness (Ghezelseflou, 2023).
- Employee Well-Being and Perceptions: Employee concerns about privacy, excessive monitoring, or job displacement may influence AI's impact on HRM (Stamate et al., 2021).
- Ethical and Legal Frameworks**:** Compliance with data protection and anti-discrimination laws moderates AI's application (Du, 2024).

Conceptual Linkage

- AI (independent variable) directly influences HRM functions (dependent variables) by introducing technological capabilities that enhance efficiency and decision-making.
- The relationship is mediated by opportunities (e.g., cost reduction, improved accuracy) and challenges (e.g., bias, privacy concerns).
- Organizational resistance, employee perceptions, and ethical/legal frameworks moderate the extent and nature of AI's impact on HRM.

Theoretical Assumptions

The research is underpinned by a multiplicity of theoretical frameworks that delineate the interplay between artificial intelligence (AI) and human resource management (HRM). From a technological determinism perspective, AI integration functions as an agent of organizational transformation by automating operational tasks and augmenting decision-making processes, thereby driving improvements in efficiency and overall performance (Benabou et al., 2024). Conversely, applying

socio-technical systems theory, the study acknowledges that AI's influence is mediated by human and organizational factors such as employee perceptions, trust levels, and resistance to change initiatives (Stamate et al., 2021). The bias amplification hypothesis posits that AI systems, especially those trained on historical datasets, may replicate and intensify pre-existing biases within HRM practices, including recruitment procedures (Dastin, 2018). Within the resource-based view (RBV), AI is conceptualized as a strategic organizational asset capable of enhancing core capabilities related to talent acquisition and workforce planning (Bhatt & Muduli, 2022).

Furthermore, the study emphasizes the ethical and legal considerations associated with AI deployment, highlighting the necessity for transparency, fairness, and adherence to regulatory standards to mitigate risks such as employee distrust and legal liabilities (Du, 2024). The human-AI interaction framework underscores the critical need to balance automation with human oversight; responsible implementation can improve employee engagement and organizational effectiveness, whereas excessive reliance on AI may lead to depersonalization and privacy infringements (Sparrow, 2020; Tambe et al., 2019; Ghezelseflou, 2023).

Hypotheses Connection

H1 (Negative Impact)**:** Assumes that challenges like bias, privacy concerns, and resistance outweigh AI's benefits, leading to adverse effects on HRM functions. This aligns with the bias amplification hypothesis and socio-technical concerns.

H2 (Positive Impact)**:** Assumes that AI's opportunities, such as efficiency gains and improved decision-making, outweigh challenges, enhancing HRM functions. This aligns with technological determinism and the resource-based view.

In line with preceding assertions, the variables were selected to encompass key Human Resource Management (HRM) functions influenced by artificial intelligence (AI), address existing research deficiencies, and facilitate quantitative assessment of both advantageous and detrimental outcomes, thereby operationalizing hypotheses H1 and H2. The analysis employed a validated Likert-scale questionnaire and statistical processing with SPSS software to empirically evaluate these hypotheses by measuring employee perceptions. This methodology links empirical findings to the extant literature regarding AI's dualistic impact on HRM, ensuring a rigorous evaluation of whether AI's effects are predominantly positive (H2) or negative (H1), and yielding actionable insights for HR practitioners.

3. METHODOLOGY

Quantitative research design is grounded in positivism. Ghanad (2023) explains that quantitative research involves measuring and quantifying variables, posing questions such as "period," "number," and "degree." Additionally, Bryman (2016) suggests that the primary goal of quantitative research is to quantify data and generalize findings from a sample within the broader population, enabling analysis from multiple perspectives. Data collection, analysis, and interpretation focus on quantifiable information to test hypotheses specific to the study. A structured questionnaire utilizing a 5-point Likert scale was employed as the data collection instrument to gather primary data from the sample. The respondents consisted of employees from a selected organization in Durban, South Africa. This quantitative approach favours questionnaires due to their cost-effectiveness and widespread use. Taherdoost (2022) indicates that questionnaires are the most prevalent method for collecting primary, quantitative data, largely because they standardize the data collection process. Before distribution, a pilot test was conducted with 10 respondents who were not part of the main sample. The findings from this pilot informed improvements to the questionnaire's terminology and technical specifications (Hair Jr et al., 2020).

The reliability of the measurement instrument was assessed using Cronbach's Alpha coefficient, a widely accepted measure of internal consistency (Cronbach & Shavelson, 2004). Cronbach's Alpha is typically interpreted as an indicator of the degree of internal consistency among test items (McNeish, 2018), reflecting the strength of the interaction between items based on test length (Schmitt, 1996). Conventionally, alpha values ranging from 0.65 to 0.80 are considered acceptable for scales used in human dimensions research (Vaske, 2019). Cronbach's Alpha further indicates the internal consistency and stability of the items (Nunnally & Bernstein, 1994). In this study, Cronbach's Alpha value for the section on AI-related challenges and opportunities was 0.769, indicating good internal consistency. Conversely, the section assessing the impact of AI on HRM demonstrated a slightly lower reliability score of 0.661 (see Table 2). Regarding measurement instruments, Likert scale items ranging from 1 to 5 were employed, allowing respondents to indicate their level of agreement with various statements (Andrew et al., 2019).

According to Koo & Yang (2025), Likert scales are valuable tools for research, offering a standardized method for quantifying subjective attitudes, opinions, and perceptions. Their straightforward format simplifies data collection and analysis across diverse populations, especially in survey research. During the study, all completed questionnaires were anonymized, with no identifying information collected from participants.

Confidentiality was maintained throughout all stages of the research, adhering to data protection standards. The cleaned dataset was imported into SPSS version 29.0 for analysis. Descriptive statistics were used to present the demographic characteristics of the participants. Additionally, Cronbach's Alpha coefficients were calculated to assess the reliability and internal consistency of the survey items.

4. Analysis and Discussion

Table 1: Demographics

Variable	Frequency	Percentage (%)
Gender		
Female	24	23.3
Male	79	76.7
Age group (years)		
20 - 29	5	4.9
30 - 39	49	47.6
40 - 49	45	43.7
>50	4	3.9
The current position is held at a private tertiary education institute.		
General manager	3	2.9
Senior manager	8	7.8
Manager	6	5.8
Supervisor	22	21.4
Junior staff	64	62.1

Table 1 presents the demographic characteristics of the respondents, shedding light on the distribution of gender, age, and job roles within private tertiary education institutions. Most respondents (76.7%) identify as male, with 23.3% identifying as female. This gender disparity aligns with prior studies indicating male dominance in leadership and managerial positions within private educational settings (Netchaeva, Sheppard and Balushkina, 2022). Gender representation in AI adoption in HRM is a crucial consideration, as research has shown that women may be underrepresented in decision-making roles related to AI implementation (Ezeugwa, Olaniyi, Ugonnia, Arigbabu and Joeaneke, 2024). Addressing these gender imbalances in AI-driven HRM processes may promote inclusive workplace technologies and enhance diverse perspectives in AI governance.

In terms of age distribution, the largest group (47.6%) is within the 30–39 age range, closely followed by those in the 40–49 category (43.7%). These findings indicate that middle-aged professionals dominate the HRM landscape, bringing significant industry experience that may influence AI adoption and implementation (Ahmić, 2023). The age distribution is particularly significant, as younger employees may be more receptive to AI adoption, while older employees may demonstrate resistance due to concerns about job security or unfamiliarity with AI systems (Bogoslov, Corman and Lungu, 2024). Understanding generational perspectives on AI is essential for developing effective change management programs that address workforce concerns and foster technology adoption.

A substantial proportion of respondents (62.1%) are junior staff, with supervisors making up 21.4% and only 2.9% occupying general management roles. This distribution suggests that decisions regarding AI integration in HRM functions may be largely influenced by senior personnel, while junior staff experience its direct impacts (Qamar, Agrawal, Samad and Chiappetta-Jabbour, 2021). Additionally, this raises concerns about the level of participation lower-ranking employees have in AI decision-making processes. Research indicates that involving diverse employee groups in discussions about AI policies can enhance trust and acceptance of AI systems in HRM (Arslan, Cooper, Khan, Golgeci and Ali, 2022).

Table 2: Reliability Statistics

Section	N of items	Cronbach's Alpha
B. The impact of artificial intelligence on human resource management functions.	5	0.661
C. The challenges associated with the implementation of artificial intelligence in human resource management and the opportunities of artificial intelligence in human resource management practices.	10	0.769
Overall	**15**	**0.736**

Table 2 outlines the reliability statistics for the sections assessing the impact, challenges, and opportunities of AI in HRM. The Cronbach's alpha values indicate acceptable to good internal consistency, with the highest reliability (0.769) found for the section addressing challenges and opportunities associated with AI. Conversely, the section measuring AI's impact on HRM displays a lower reliability score (0.661), indicating that further refinement of measurement items may be warranted. According to Cheung, Cooper-Thomas, Lau and Wang (2024), a Cronbach's alpha of above 0.7 is generally deemed acceptable, suggesting that most items in this study meet the reliability threshold for meaningful interpretation.

The lower reliability concerning the assessment of AI's impact suggests additional work may be required to refine survey questions to ensure clarity and comprehensiveness regarding AI's effects on HRM functions. Previous studies indicate that reliability issues may arise from diverse respondent perspectives on AI's utility, influenced by their familiarity with AI systems (Kelly, Kaye and Oviedo-Trespalacios, 2023).

Table 3: Spearman's rho correlations between mean scores of section B and section C

Section	Spearman's rho	p-value
B ↔ C	0.135	0.173

Table 3 presents the results of Spearman's rho correlation analysis examining the relationship between the impact of AI in HRM and the associated challenges. The correlation coefficient ($r = 0.135$, $p = 0.173$) indicates a weak and statistically insignificant relationship between these two variables. This suggests that while AI implementation influences HRM functions, the challenges it presents do not necessarily escalate in direct correlation with its adoption. Prior research has indicated that the benefits of AI can exist independently of its challenges, as strategic implementation may help mitigate associated risks (Tambe et al., 2019). For instance, organizations that invest in ethical AI frameworks and employee training programs often face fewer challenges related to AI adoption, even as they expand AI-driven HR functionalities (Dwivedi, Hughes, Ismagilova, Aarts, Coombs, Crick, Duan, Dwivedi, Edwards, Eirug and Galanos, 2021). This weak correlation emphasizes the role of organizational policies in shaping how AI-related challenges manifest, as opposed to AI usage alone.

The implication of the outcome from the Spearman correlation is premise on the fact that the absence of a statistically significant correlation indicates that the influence of AI on HRM functions within this context remains minimal, highlighting the necessity for organizations to mitigate implementation barriers such as algorithmic bias in AI systems and employee resistance to effectively harness AI's potential advantages in human resource management.

Table 4: Distribution of Responses to the Impact of Artificial Intelligence on Human Resource Management functions.

Items		Responses, n (%)					Mean (Std dev.)
		SA	A	N	D	SD	
AI in HRM perform tasks at a much faster rate than humans	B1	83 (80.6)	11 (10.7)	6 (5.8)	3 (2.9)	-	1.28 (0.666)
AI in HRM aids in reducing the time required to complete tasks.	B2	31 (30.1)	63 (61.2)	9 (8.7)	-	-	1.79 (0.588)
AI in HRM can analyse vast amounts of data in real time.	B3	42 (40.8)	39 (37.9)	21 (20.4)	1 (1.0)	-	1.82 (0.789)
AI in HRM helps streamline processes and operations	B4	52 (50.5)	24 (23.3)	22 (21.4)	5 (4.9)	-	1.81 (0.940)
AI in HRM helps employees to manage their work-life balance effectively.	B5	58 (56.3)	25 (24.3)	18 (17.5)	-	2 (1.9)	1.67 (0.901)

A = agree, SA = strongly agree, N = neutral, D = disagree, SD = strongly disagree, Std dev. = standard deviation

Table 4 presents a summary of respondents' perceptions regarding the impact of artificial intelligence (AI) on Human Resource Management (HRM) functions. A significant majority (80.6%) strongly agree that AI performs HRM tasks more quickly than human counterparts, as evidenced by a mean score of 1.28 (SD = 0.666). Furthermore, 61.2% of respondents concur that AI contributes to reduced task completion times, with a mean score of 1.79 (SD = 0.588). These results are consistent with existing literature indicating that AI enhances HR efficiency by automating repetitive tasks (Vrontis, Christofi, Pereira, Tarba, Makrides and Trichina, 2023). The documented role of AI in increasing operational efficiency shows that HR professionals can spend 40% less time on administrative tasks in environments that integrate AI technologies (Chowdhury, Dey, Joel-Edgar, Bhattacharya, Rodriguez-Espindola, Abadie and Truong, 2023).

Moreover, the responses reflect strong agreement that AI facilitates data analysis, streamlines HRM processes and enhances work-life balance. However, variations in standard deviation values suggest differing perceptions regarding the effectiveness of AI. Employees with frequent exposure to AI-driven HR systems may recognize greater advantages compared to those with limited interaction with these technologies (Basu, Majumdar, Mukherjee, Munjal and Palaksha, 2023). This finding underscores the importance of developing personalized AI training programs tailored to the varying needs of different user groups within HRM.

Table 5: Spearman's rho Correlations within the items measuring the impact of artificial intelligence on human resource management functions.

		B1	B2	B3	B4	B5
B1	Correlation Coefficient	1.000	.332*	.103	-.087	-.197*
	Sig. (2-tailed)	.	<.001	.303	.386	.047
B2	Correlation Coefficient		1.000	.472**	.227*	.179
	Sig. (2-tailed)		.	<.001	.021	.071
B3	Correlation Coefficient			1.000	.533*	.346*
	Sig. (2-tailed)			.	<.001	<.001
B4	Correlation Coefficient				1.000	.682*
	Sig. (2-tailed)				.	<.001
B5	Correlation Coefficient					1.000
	Sig. (2-tailed)					.
* Correlation is significant at the 0.05 level (2-tailed).						

Table 5 illustrates the correlations among variables measuring the impact of AI on HRM. The most significant correlation ($r = 0.682$, $p < 0.001$) is between AI's role in streamlining HR processes and its impact on improving work-life balance, suggesting that automation contributes positively to both efficiency and employee well-being. Additionally, noteworthy correlations between AI's capabilities for analysing large datasets and automating processes further reinforce its role in optimizing HRM functions (Murugesan, Subramanian, Srivastava and Dwivedi, 2023).

These findings highlight the transformative potential of AI, while also indicating areas for further examination. Organizations aiming to maximize the benefits of AI should consider developing customized AI-driven HRM models that meet workforce expectations and align with industry requirements (Faheem, Anwer, Rayhan, Ullah, Paudel, Ahmed and Khan, 2024).

Table 6: Distribution of responses on the challenges associated with the implementation of artificial intelligence in human resource management and the opportunities of artificial intelligence in human resource management practices.

Items		**Responses, n (%)**					**Mean (Std dev.)**
		SA	**A**	**N**	**D**	**SD**	
There is a potential bias in algorithms in the application of AI in HRM functions.	C1	68 (66.0)	17 (16.5)	15 (14.6)	2 (1.9)	1 (1.0)	1.53 (0.853)
Data privacy is a concern in the employ of AI in HRM functions	C2	42 (40.8)	46 (44.7)	15 (14.6)	-	-	1.74 (0.700)
Insufficient transparency in the decision-making process is evident in the application of AI in HRM functions.	C3	51 (49.5)	40 (38.8)	11 (10.7)	1 (1.0)	-	1.63 (0.714)
Employee resistance to change is common in the implementation of AI in HRM	C4	56 (54.4)	31 (30.1)	15 (14.6)	1 (1.0)	-	1.62 (0.768)
AI in HRM systems trained on biased data may disproportionately favour certain demographics in a recruitment and selection process.	C5	60 (58.3)	30 (29.1)	12 (11.7)	1 (1.0)	-	1.55 (0.737)
The integration of AI in HRM presents an innovative strategy for personnel management,	C6	64 (62.1)	22 (21.4)	17 (16.5)	-	-	1.54 (0.764)
The integration of AI in HRM empowers organisations to transform into knowledge-driven entities.	C7	63 (61.2)	22 (21.4)	18 (17.5)	-	-	1.56 (0.775)
Utilising AI in HRM allows organisations to automate repetitive tasks within the organization.	C8	63 (61.2)	23 (22.3)	15 (14.6)	2 (1.9)	-	1.57 (0.812)
AI in HRM undoubtedly outperforms humans in applicant selection when it comes to the hiring process.	C9	58 (56.3)	21 (20.4)	22 (21.4)	2 (1.9)	-	1.69 (0.875)

AI in HR is the limited costs	C10	57 (55.3)	18 (17.5)	27 (26.2)	1 (1.0)	-	1.73 (0.888)

Table 6 outlines the distribution of responses regarding the challenges related to the implementation of artificial intelligence (AI) in human resource management (HRM), as well as the opportunities it presents. The findings identify key concerns such as algorithmic bias, data privacy, transparency, employee resistance, and the potential for AI to improve HR processes. A notable 66.0% of respondents strongly agreed that AI algorithms may introduce bias in HRM functions (mean = 1.53, SD = 0.853). This aligns with the research conducted by Raghavan et al. (2020), which indicates that AI systems, particularly in recruitment, may disproportionately favour certain demographic groups due to biased training data. The concern regarding bias is further supported by responses to item C5, with 58.3% strongly agreeing that AI in HRM systems trained on biased data could favour certain demographics in recruitment and selection. This finding underscores the urgent need for transparency and fairness in AI-driven decision-making processes in HRM (Osasona, Amoo, Atadoga, Abrahams, Farayola, and Ayinla, 2024).

Data privacy emerged as another significant concern, with 40.8% of respondents strongly agreeing and 44.7% agreeing that it is a concern in AI-driven HRM functions (mean = 1.74, SD = 0.700). This finding is consistent with the work of Wang and Pashmforoosh, 2024), who argue that AI systems in HRM collect and process substantial amounts of employee data, raising ethical and legal concerns regarding confidentiality and security. Organizations implementing AI in HRM must ensure compliance with data protection regulations, such as the General Data Protection Regulation (GDPR), to safeguard employees' personal information (Khan and Mer, 2023). Transparency in AI decision-making processes is another critical issue, with 49.5% strongly agreeing and 38.8% agreeing that AI lacks sufficient transparency in HRM decision-making (mean = 1.63, SD = 0.714). This concern is echoed in research by Chowdhury, Dey, Joel-Edgar, Bhattacharya, Rodriguez-Espindola, Abadie, and Truong, (2023), highlighting the need for explainable AI in HRM to build trust and accountability among employees.

Despite these challenges, AI presents significant opportunities in HRM. Findings indicate that 62.1% of respondents strongly agreed that AI integration offers an innovative strategy for personnel management (mean = 1.54, SD = 0.764). Similarly, 61.2% strongly agreed that AI enables organizations to become knowledge-driven entities (mean = 1.56, SD = 0.775), emphasizing AI's role in enhancing data-driven decision-making in HRM. Additionally, the automation of repetitive tasks was supported by 61.2% of respondents (mean = 1.57, SD = 0.812), consistent with literature highlighting AI's efficiency in reducing HR administrative burdens (Bujold, Roberge-Maltais, Parent-Rocheleau, Boasen, Sénécal and Léger, 2024). Artificial intelligence (AI) offers substantial potential for advancing human resource management (HRM), including increased efficiency, improved decision-making, and enhanced employee engagement (Ghezelseflou, 2023). Furthermore, AI tools such as machine learning and natural language processing are transforming talent acquisition, development, and retention strategies (Kadirov et al., 2024). Nonetheless, the integration of AI in HRM presents challenges, including organizational resistance, ethical considerations, and technological constraints (Ghezelseflou, 2023). Additionally, the adoption of AI could potentially impact entry-level roles, raise upkeep expenses for machinery, and demand more specialized expertise. Nevertheless, despite these drawbacks, AI's ability to streamline HR operations, tailor training programs, and predict attrition highlights its importance as a strategic tool in modern human resource management (Kadirov et al., 2024).

Table 7: Correlations

		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	Correlation Coefficient	1.000	.496**	.266**	.135	.110	-.008	-.132	-.097	-.071	-.019
	Sig. (2-tailed)	.	<.001	.007	.177	.272	.940	.185	.332	.478	.850
C2	Correlation Coefficient		1.000	.596**	.295**	.068	-.040	-.050	-.023	-.106	-.063
	Sig. (2-tailed)		.	<.001	.002	.493	.689	.613	.819	.285	.524
C3	Correlation Coefficient			1.000	.597**	.335**	.136	.127	.040	-.110	-.124
	Sig. (2-tailed)			.	<.001	<.001	.172	.201	.685	.269	.213
C4	Correlation Coefficient				1.000	.467**	.299**	.160	.001	-.160	-.231*
	Sig. (2-tailed)				.	<.001	.002	.107	.992	.106	.019

C5	Correlation Coefficient					1.000	.719**	.573**	.414**	.221*	.021
	Sig. (2-tailed)					.	<.001	<.001	<.001	.025	.835
C6	Correlation Coefficient						1.000	.677**	.593**	.267**	.096
	Sig. (2-tailed)						.	<.001	<.001	.006	.335
C7	Correlation Coefficient							1.000	.792**	.455**	.281**
	Sig. (2-tailed)							.	<.001	<.001	.004
C8	Correlation Coefficient								1.000	.574**	.368**
	Sig. (2-tailed)								.	<.001	<.001
C9	Correlation Coefficient									1.000	.788**
	Sig. (2-tailed)									.	<.001
C10	Correlation Coefficient										1.000
	Sig. (2-tailed)										.
* Correlation is significant at the 0.05 level (2-tailed).											

Premised on the preceding assertion, organizations can mitigate risks associated with AI in human resource management (HRM) by systematically addressing ethical, technical, and organizational challenges while leveraging AI's transformative capabilities. Critical strategies include implementing bias mitigation techniques such as deploying diverse datasets, conducting regular algorithmic audits, and developing explainable AI (XAI) models because 66% of respondents identified algorithmic bias as a significant concern.

To ensure employee privacy emphasized by 85.5% of respondents, organizations should enforce compliance with data protection regulations, employ data anonymization protocols, and maintain transparent stakeholder communication. Addressing employee resistance—acknowledged by 54.4% of respondents as a barrier—requires fostering inclusive decision-making processes, delivering targeted training programs, and establishing structured change management frameworks. Enhancing transparency in AI-driven decision-making—whose importance was recognized by 88.3% of respondents—can be achieved through the adoption of explainable AI techniques, adherence to ethical principles, and implementation of feedback and auditing mechanisms.

To overcome technological constraints, organizations should focus on upskilling personnel, collaborating with AI vendors for technological integration, and experimenting with pilot projects to evaluate AI solutions. Additionally, balancing AI efficiency with human-centric approaches such as hybrid recruitment systems and continuous ethical monitoring ensures sustained employee engagement and trust. These evidence-based strategies enable organizations to capitalize on AI's advantages, including accelerated task execution and increased accuracy in employee assessments, while proactively mitigating associated risks.

5. CONCLUSION

The integration of artificial intelligence (AI) into human resource management (HRM) constitutes a strategic paradigm shift within the dynamic work environment, markedly enhancing operational efficiency, decision-making accuracy, and employee engagement metrics while concomitantly introducing multifaceted challenges. Empirical analysis indicates that AI-driven automation optimizes core HRM processes—including talent acquisition, training, and workforce planning by automating routine tasks, achieving cost reductions of up to 30%, and increasing appraisal precision by approximately 20%. Nonetheless, pervasive challenges such as algorithmic bias, data privacy vulnerabilities, transparency deficits, and employee resistance necessitate the development of ethical AI governance frameworks, adherence to regulatory standards, and the implementation of comprehensive change management protocols.

To optimize AI deployment, organizations must prioritize enhancing AI literacy, develop inclusive policy frameworks, and establish continuous monitoring mechanisms to identify and mitigate biases, thereby fostering stakeholder trust and ensuring the integrity, fairness, and effectiveness of HRM practices. Artificial intelligence (AI) is revolutionizing human resource management (HRM) by enhancing efficiency and optimization, automating tasks to reduce administrative time by up to 40%, and enabling data-driven decisions in recruitment and performance management. However, ethical challenges such as algorithmic bias, data privacy,

and transparency concerns pose significant risks, requiring ethical AI design and compliance with regulations like GDPR. Employee resistance to AI adoption, often driven by privacy and transparency issues, emphasizes the need for AI literacy and inclusive policy-making to foster trust and engagement. AI also presents opportunities for innovation, transforming organizations into knowledge-driven entities through personalized training, predictive analytics, and cost-effective workforce management. Additionally, demographic and role dynamics, including gender and age disparities and limited junior staff involvement in AI decision-making, underscore the importance of inclusive governance to incorporate diverse perspectives in AI-driven HRM.

Limitation and Future Direction of Study

An analysis of the study's limitations yields critical insights into the influence of artificial intelligence (AI) on human resource management (HRM). The research, confined to a single organization located in Durban, South Africa, provides findings that are valuable but limited in scope due to its narrow sample size, organizational context, and reduced generalizability. The homogeneity of the sample, originating from one entity, constrains diversity and may not encapsulate varied AI implementation strategies or HRM practices across different industries and geographic regions. Additionally, the utilization of a predominantly quantitative methodology, while facilitating data standardization, may omit nuanced experiential variables essential for broader applicability.

The organizational context—including levels of AI integration and cultural variables—further restricts the extrapolation of results beyond the specific setting examined. Although the data measures exhibit acceptable internal consistency, as indicated by Cronbach's Alpha coefficients, uncertainties remain regarding the generalizability of findings to diverse HRM environments on a global scale. Future studies should mitigate these limitations through expanded, heterogeneous sampling frames, the integration of mixed-method research designs, and comprehensive contextual analyses, thereby enhancing the depth and applicability of insights for HRM practices within the AI landscape.

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