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A Study on Human-AI Interaction and Strategic HRM Practices: Challenges and Potential

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Abstract

The rapid integration of artificial intelligence (AI) in organizational practices has transformed human resource management (HRM), demanding a nuanced understanding of AI–human interaction within strategic and operational HR functions. This study investigates the determinants of AI adoption in HRM, focusing on both organizational and HR role-related factors. A structured survey-based research design was employed, targeting senior HR professionals—including HR Heads, Managers, and Chief Human Resource Officers (CHROs)—drawn from a professional HR database. After rigorous data screening, valid responses were retained for analysis. The study examined major AI adoption determinants, including Behavioural Intention, Top Management Support, Performance Expectancy, and Competitive Pressure. Additionally, it considered critical HRM role dimensions derived from Ulrich's model, such as Administrative Expert, Employee Champion, Strategic Partner, and Change Agent. Measurement items were refined from established constructs and assessed using a five-point Likert scale. Descriptive statistics revealed that respondents exhibited positive attitudes toward AI adoption, reflecting expectations of efficiency gains and improved decision-making. Validity and reliability analysis confirmed the robustness of the measurement instrument. Hypothesis testing using structural equation modeling demonstrated that all proposed hypotheses were supported, highlighting the significant influence of both organizational factors and HRM role responsibilities on AI adoption. The findings suggest that alignment of strategic objectives, managerial support, and change facilitation synergistically enhances AI–human collaboration. This study provides empirical evidence for practitioners and policymakers to design effective AI-driven HR strategies that optimize talent management, operational efficiency, and organizational competitiveness.

Keywords: AI adoption, HRM roles, Behavioural Intention, Performance Expectancy, Top Management Support, Competitive Pressure, Strategic Partner, Change Agent, organizational transformation, human–AI collaboration

Introduction

Artificial Intelligence (AI) has emerged as a cornerstone of the Fourth Industrial Revolution, often referred to as "Industry 4.0" (Kong et al., 2021). With continuous advancements in information and communication technologies (ICT), AI has begun to profoundly influence multiple dimensions of contemporary organizational life. These developments are reshaping work environments characterized by increasing technological intensity, accelerated innovation cycles, and heightened digital interactions within the gig economy (Glikson & Woolley, 2020). Such changes have created a dynamic and complex ecosystem where both managers and employees must constantly adapt to evolving technologies.

The integration of AI into workplace operations has generated a dual impact—introducing substantial advantages while also presenting novel challenges. As Meister (2019) highlighted in a *Forbes* article, "the next phase of HR is both AI and human," underscoring how technology is not merely a supportive tool but a transformative force redefining human resource management (HRM). Historically, HRM evolved from the industrial era's mechanization processes, where human labor—either physical or cognitive—underwent gradual technological substitution (Luo et al., 2019). However, modern AI advancements have introduced more sophisticated alternatives that can replicate, complement, or even surpass certain human functions.

AI-powered systems and robotic process automation (RPA) have begun to alter traditional HR structures and employment patterns, challenging existing notions of job design and organizational roles (Larivière et al., 2017). Despite the disruptive potential, these technologies also provide vast opportunities for HRM to enhance operational efficiency, talent analytics, and employee engagement. Tools such as machine learning (ML), the Internet of Things (IoT), and smart devices have enabled multinational corporations to improve communication, coordination, and collaboration across borders (Cooke et al., 2019). Furthermore, the evolution of digital Human Resource Information Systems (HRIS) has streamlined numerous HR functions, from candidate screening and onboarding to performance appraisal and workforce planning (Abraham et al., 2019).

In this context, the present study aims to analyze the emerging challenges HR professionals face in balancing human–AI collaboration within modern organizations. It also seeks to identify actionable strategies that promote synergy between AI-driven systems and human employees at both individual and group levels, offering insights for sustainable HRM transformation.

Review of Literature

Existing studies have extensively discussed the implications of AI adoption in HRM, focusing primarily on workforce displacement, evolving skill requirements, and changes in talent management dynamics (Coupe, 2019). A survey by KPMG (2019) revealed an intriguing dichotomy—while a majority of CEOs believe AI will ultimately create more employment opportunities, HR practitioners often view AI as a disruptive force that could render certain roles redundant. This perception gap reflects a long-standing operational perspective within HR departments, where technological innovations are primarily associated with reskilling initiatives for employees at risk of automation (Libert et al., 2020).

Driskell et al. (2018) emphasized that successful collaboration within teams depends heavily on psychological factors such as cognitive biases, personality traits, and interpersonal sensitivity. These factors become even more complex when humans and AI systems work side by side, as employees may exhibit resistance or anxiety regarding potential job loss and reduced autonomy. Such psychological barriers often hinder the effective integration of AI tools into HR functions (Jurczyk-Bunkowska & Pawełoszek, 2015).

The fusion of AI and human collaboration therefore poses distinctive challenges for HRM in modern enterprises. HR professionals must not only address employees' concerns about job displacement but also develop mechanisms to foster trust, ethical alignment, and transparent communication between AI-driven systems and human co-workers (Arslan et al., 2020).

Recent literature further asserts that AI is no longer merely an auxiliary tool for administrative efficiency—it is becoming a strategic enabler for organizational transformation. AI-assisted HRM enables predictive workforce analytics, data-driven decision-making, and personalized employee experiences, which collectively enhance organizational performance (Malik et al., 2022).

The Emerging Role of AI in HRM

Beyond automating routine tasks, AI is increasingly shaping strategic HR functions such as succession planning, diversity management, and employee well-being. AI algorithms can now predict attrition trends, identify leadership potential, and design adaptive learning pathways tailored to individual competencies. This paradigm shift positions HRM as a data-centric, analytics-driven function where human judgment and machine intelligence operate synergistically. As organizations transition toward hybrid human–AI ecosystems, the future of HRM will depend on developing ethical frameworks, emotional intelligence training, and reskilling strategies that ensure humans remain central to the evolving digital workplace.

Research Methodology

The proposed hypotheses were empirically examined through a structured survey-based research design. The sampling framework was formulated using secondary data obtained from the Human Resource Management Association, which provided access to a diverse pool of senior HR professionals across various organizations. As the core objective of this study was to explore the dynamics of AI–human interaction within HRM practices, it was essential to target respondents who possess strategic decision-making authority and directly influence their organizations' technology adoption initiatives. Consequently, the study focused on senior-level HR executives such as HR Heads, Managers, and Chief Human Resource Officers (CHROs).

A total of 192 participants were initially selected for the study. After rigorous data screening to ensure completeness and validity, 186 responses were retained for final analysis, while six responses were discarded due to inconsistencies or missing information. The survey was administered in English, ensuring linguistic clarity and accessibility. Respondent anonymity was strictly maintained to uphold ethical standards and encourage unbiased participation.

The measurement instrument was adapted from established constructs used in previous empirical investigations on human–AI collaboration and information technology adoption, each of which has consistently demonstrated strong reliability and construct validity. The measurement items were subsequently contextualized and refined to align with the specific objectives of the present study.

The study considered four major adoption determinants:

- Behavioural Intention (BI)
- Top Management Support (TMS)
- Performance Expectancy (PE)
- Competitive Pressure (CP)

Additionally, the research model incorporated four essential HRM role dimensions, originally conceptualized by Ulrich (1998) — namely, Administrative Expert (AE), Employee Champion (EC), Strategic Partner (SP), and Change Agent (CA). For the purposes of analytical precision, these constructs were streamlined into twenty validated indicators, each assessed through a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5).

The study hypothesizes the following relationships among variables:

- **H1:** Competitive Pressure (CP) has a positive association with AI–human interaction in HRM.
- **H2:** Top Management Support (TMS) positively influences behavioural intention toward AI–human interaction in HRM.
- **H3:** Performance Expectancy (PE) positively affects the behavioural intention to engage in AI–human interaction within HRM.
- **H4:** The Strategic Partner (SP) role of HRM is positively correlated with AI–human interaction in HRM.
- **H5:** The Change Agent (CA) role of HRM is positively related to AI–human interaction in HRM.

Through this methodological approach, the study endeavours to capture both the behavioural and strategic underpinnings of AI adoption in HRM, thereby providing deeper insights into how organizational structures evolve under the influence of human–AI collaboration.

Data Analysis and Interpretation

Table 1: Demographic Profile of Respondents

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	112	60.2
	Female	74	39.8
Age (years)	25–34	40	21.5
	35–44	78	41.9
	45–54	52	28.0
	55 and above	16	8.6

Demographic Variable	Category	Frequency	Percentage (%)
Educational Qualification	Bachelor’s Degree	36	19.4
	Master’s Degree	122	65.6
	Doctorate/PhD	28	15.0
Current Designation	HR Manager	80	43.0
	HR Head/Director	70	37.6
	CHRO	36	19.4
Years of Experience	1–5	22	11.8
	6–10	48	25.8
	11–15	72	38.7
	16 and above	44	23.7

Table 1 explained the demographic profile reveals a well-balanced and strategically relevant respondent pool for assessing AI adoption in HRM. Gender distribution shows 60.2% male and 39.8% female respondents, indicating a moderate gender diversity within senior HR positions. Age-wise, the majority of participants (41.9%) fall in the 35–44-year bracket, reflecting mid-to-senior-level professionals who are typically responsible for strategic technology adoption. Educational qualifications are skewed toward higher education, with 65.6% holding a master’s degree, suggesting that respondents possess the requisite academic foundation to evaluate complex HRM and AI integration processes. Regarding professional roles, 43% are HR Managers, 37.6% are HR Heads/Directors, and 19.4% are CHROs, ensuring that insights are drawn from individuals with decision-making authority. The experience distribution shows that 38.7% have 11–15 years, while 23.7% have more than 16 years of experience, highlighting a seasoned cohort capable of evaluating both operational and strategic HR initiatives. Lastly, organizational size is well represented across small, medium, and large enterprises, ensuring that findings are generalizable across diverse corporate contexts. Overall, the demographic composition validates the study’s focus on senior HR professionals, providing a credible foundation for examining AI–human interaction within HRM.

Table 2: Descriptive Statistics of Key Constructs

Construct	Mean	Std. Deviation
Behavioural Intention (BI)	4.12	0.61
Top Management Support (TMS)	3.98	0.72
Performance Expectancy (PE)	4.05	0.66
Competitive Pressure (CP)	3.75	0.81

Construct	Mean	Std. Deviation
Administrative Expert (AE)	3.88	0.69
Employee Champion (EC)	3.92	0.70
Strategic Partner (SP)	4.01	0.64
Change Agent (CA)	3.84	0.73

Table 2 explained the descriptive statistics reveal positive attitudes toward AI adoption among senior HR professionals. Behavioural Intention (BI) exhibits a high mean of 4.12, indicating that respondents are inclined to adopt AI tools within HRM practices. Top Management Support (TMS) scores 3.98, reflecting strong executive backing for AI initiatives, which is critical for successful implementation. Performance Expectancy (PE) has a mean of 4.05, suggesting that HR leaders anticipate tangible efficiency gains, improved decision-making, and better talent management outcomes through AI integration. Competitive Pressure (CP) registers a slightly lower mean of 3.75, indicating that while external market forces influence adoption, internal motivation and strategic alignment are more prominent drivers. Examining HR role dimensions, Administrative Expert (AE) and Employee Champion (EC) scores reflect moderate to high confidence that AI can enhance routine operations and support employee-centric initiatives. Strategic Partner (SP) achieves a mean of 4.01, highlighting that HR leaders view AI as a tool for aligning HR strategy with organizational objectives. Finally, Change Agent (CA) scores 3.84, showing recognition of AI's potential in facilitating organizational transformation. Collectively, these statistics demonstrate a favorable perception of AI among HR executives, emphasizing both operational and strategic benefits.

Table 3: Measures of Validity and Reliability

Constructs	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Behavioural Intention (BI)	0.912	0.931	0.765
Top Management Support (TMS)	0.895	0.920	0.742
Performance Expectancy (PE)	0.888	0.914	0.730
Competitive Pressure (CP)	0.721	0.802	0.612
Administrative Expert (AE)	0.927	0.938	0.770
Employee Champion (EC)	0.918	0.933	0.758
Strategic Partner (SP)	0.910	0.925	0.743
Change Agent (CA)	0.902	0.919	0.735

Table 3 examined validity and reliability measures demonstrate strong psychometric properties of the constructs used in this study. Cronbach's alpha values range from 0.721 (Competitive Pressure) to 0.927 (Administrative Expert), all exceeding the commonly accepted threshold of 0.70, indicating good internal consistency across constructs. This confirms that the survey items reliably measure their respective latent variables. Composite Reliability (CR) values range from 0.802 to 0.938, further validating the internal consistency and confirming that the constructs have stable factor loadings. The Average Variance Extracted (AVE) scores, ranging from 0.612 to 0.770, exceed the minimum threshold of 0.50, demonstrating adequate convergent validity. Specifically, constructs such as Behavioural Intention (0.765) and Administrative Expert (0.770) indicate that the majority of item variance is captured by the latent variable, supporting construct validity. Even Competitive Pressure, which has relatively lower reliability, maintains acceptable AVE and CR values, suggesting it still contributes meaningfully to the measurement model. Collectively, these statistics indicate that the measurement instrument is both reliable and valid for capturing AI adoption determinants and HRM role dimensions. The high validity and reliability provide a solid foundation for subsequent structural equation modeling and hypothesis testing, ensuring confidence in the study's empirical results.

Table 4: Results of Hypothesis Testing

Hypothesis	Constructs	Standardized Coefficient (β)	Standard Error (SE)	Critical Ratio (CR)	p-value	Outcome
H1	CP	0.11	0.05	3.10	0.003	Accepted
H2	TMS	0.12	0.05	3.20	0.002	Accepted
H3	PE	0.73	0.20	8.00	0.000	Accepted
H4	SP	0.09	0.04	3.05	0.003	Accepted
H5	CA	0.11	0.03	3.40	0.000	Accepted

Table 4 highlights that all five hypotheses are accepted, confirming the significant influence of both organizational and HR role-related factors on AI adoption. Competitive Pressure (H1) shows that external market dynamics motivate organizations to adopt AI technologies. Top Management Support (H2) emphasizes that executive endorsement and active commitment are essential for successful implementation. Performance Expectancy (H3) demonstrates the strongest impact, suggesting that HR professionals prioritize AI solutions that enhance efficiency, decision-making, and overall organizational performance.

Conclusion

This study demonstrates that AI adoption in HRM is significantly influenced by both organizational determinants and HRM role dimensions. Performance Expectancy emerged as the strongest predictor, underscoring that HR professionals prioritize AI technologies that enhance operational efficiency, improve decision-making, and support strategic outcomes. Competitive Pressure and Top Management Support further highlight that external market dynamics and executive commitment are critical enablers of AI integration. Additionally, HR roles such as Strategic Partner and Change Agent play a vital role in facilitating adoption, demonstrating that aligning HR strategy with organizational goals and actively managing change are essential for effective AI–human collaboration.

The research provides a comprehensive framework for understanding AI adoption within HRM, offering actionable insights for senior HR executives seeking to implement AI-driven solutions. By validating the influence of both behavioral and strategic factors, the study confirms that successful AI integration requires a holistic approach combining managerial support, strategic alignment, and role-based responsibilities.

Future research can extend this study by examining AI adoption across multiple industries and geographical contexts to enhance generalizability. Longitudinal studies could capture the evolving impact of AI on HR practices over time, while qualitative investigations may provide deeper insights into employee perceptions, resistance, and engagement with AI systems. Moreover, exploring the interplay between AI and emerging HR technologies such as predictive analytics, digital learning platforms, and employee experience management could provide further guidance for designing innovative, human-centered HR strategies.

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