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ARTIFICIAL INTELLIGENCE INTEGRATION AND THE TRANSFORMATION OF WORK: IMPLICATIONS FOR ORGANISATIONS

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Abstract

This study examines the incorporation of Artificial Intelligence (AI) in professional and business services, concentrating on human resource management (HRM) and its effects on organizational transformation. Using Partial Least Squares (PLS) analysis, data were gathered from 252 respondents to ascertain the principal variables affecting AI adoption, including recruitment, onboarding, employee monitoring, internal mobility, and comprehensive workplace transformation. Artificial intelligence (AI) affects human resource management (HRM), and in so doing, it is transforming the nature of work, workers and workplaces. While AI-assisted HRM is increasingly considered a strategy for improving organizational transformation to easier use for the employees, the academic literature has not yet offered a strategic framework to guide HR managers in adopting and implementing it. However, existing research in this area offers an opportunity to build such a framework. This systematic review of 30 peer-reviewed articles helps to achieve this objective. We critically examine the organizational and employee-centric outcomes of AI-assisted HRM and develop a strategic framework to guide its practice and future research.

Keywords: *Artificial Intelligence, Workplace Transformation, Augmentation, Replacement, Industry 4.0*

1. Introduction

Progress in artificial intelligence (AI) has significantly transformed the business landscape. The incorporation of AI in human resources will enhance the analysis, prediction, and diagnosis of organizational issues, thereby aiding in the formulation of improved employee-related decisions. A comprehensive synthesis of various literature streams was conducted to critically evaluate the application of AI and HR analytics in human resource management for performance improvement and competitive advantage. The HRM has experienced a significant transformation from administrative functions to advanced processes, such as automation through artificial intelligence, which has fundamentally redefined the characteristics of the organizational workforce. Artificial intelligence significantly contributes to human resources by facilitating advanced people analytics. The implementation of AI and analytics in HR functions, including talent acquisition, training and development, employee retention, engagement, and performance appraisal, enables organizations to improve efficiency and productivity. Furthermore, AI, cloud computing, and HR analytics facilitate the aggregation of substantial amounts of employee data. Human Resources is regarded as a 'predictive engine' vital for organizational advancement. The primary challenge for the HR department is the extent to which they can improve employee

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skills and restructure their teams in the domains of HR Analytics and AI. This research assesses the functional analysis of artificial intelligence within the realm of human resources. It highlights the implementation of AI in diverse HRM functions and delineates the obstacles to the adoption of HR technology among employees.

Artificial Intelligence (AI) technology has become ubiquitous. The pervasive influence of AI in contemporary society has transformed our lifestyle. The extensive implementation of AI in enterprises is facilitating process optimization, enhancing productivity, improving efficiency, and lowering expenses. The amalgamation of artificial intelligence with human resource management (HRM) practices is transforming the methods by which organizations recruit, oversee, and involve their personnel. Artificial intelligence empowers machines to make decisions with greater accuracy than humans by utilizing existing data sets and behavioral patterns. This transformation has resulted in machines assuming all manual tasks, thereby enabling HR professionals to adopt more strategic roles. Organizations and professionals need to comprehend the functionality of this technology and its significance in diverse HRM operations.

Research Objectives

- To look at how artificial intelligence is being used in human resource management around the world, especially in areas like finding new employees, helping them get started, keeping an eye on what they do and moving them to different jobs within the company.
- To see how using intelligence in human resource management affects the company and the people who work there, particularly when it comes to getting things done efficiently, being productive, making good decisions and being able to adjust to changes.
- To find out how artificial intelligence can help turn workplaces into modern and smart work environments.
- To identify what helps and what gets in the way of companies using intelligence in human resource management, including what skills employees need, how different generations feel about it and whether the company is ready for it.
- To come up with ideas for human resource managers and companies on how to use intelligence in a way that is good for everyone and does not harm the workers or the company.
- To suggest what future studies should look at to fill in the gaps in our understanding of how artificial intelligence is changing human resource management, especially in places where the economy is still developing, and workplaces are changing a lot due to technology.

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2. Literature Review

2.1 HRM Practices

A primary focus has been on the potential influence of AI and other intelligence-driven tools and methodologies on the HRM function and its subdomains. Examining the literature allowed us to concentrate on AI-enhanced HRM functions by focusing on specific sub-functional areas, including human resource planning, recruitment and selection, training and development, compensation and benefits, and performance management, and to evaluate how these AI-enabled digital functions created innovative opportunities for organizations and employees. Artificial intelligence is integral to human resources planning by assessing future workforce requirements and facilitating optimal recruitment choices. AI-driven recruitment and selection are essential for attracting and identifying the most talented workforce. AI algorithms can enhance the identification of job candidates, the dissemination of job openings, and the job interview process. AI facilitates training and development by storing employees' electronic resumes, maintaining an electronic inventory of personnel, monitoring skill deficiencies, creating appropriate training programs, and assisting organizations in identifying suitable candidates. AI systems aid HR managers in evaluating training efficacy and determining employee competency, ensuring the appropriate allocation of individuals with relevant skills to suitable roles. Automation in payroll systems assists HR professionals in effectively managing all payroll and associated value-added tasks. AI systems aid managers in gathering relevant information regarding necessary employee compensation and benefits structures. Performance management tools and techniques offer numerous opportunities for both employees and organizations, including fuzzy multi-attribute decision-making tools that assist in identifying employees requiring additional development.

2.1.1 Recruitment and Hiring

Artificial intelligence is assisting companies and recruitment agencies in operating efficiently by rapidly processing a substantial volume of candidate applications. Through the utilization of AI, companies can enhance candidate engagement and implement both high-volume and high-touch strategies, thereby fostering a stable and enduring relationship with their candidates. AI-powered bots are employed to communicate with applicants, address their inquiries, and maintain their engagement throughout the hiring process. AI-driven assistants or bots are proficient in natural language processing (NLP) and consequently, assume a prominent role in various forms of candidate communications. AI assistants are aiding recruiters in candidate screening, initiating contact, scheduling meetings and interviews, and enhancing candidate engagement. This further benefits organizations by conserving time and resources, acquiring high-calibre candidates, accurately assessing talents, minimizing bias, and promptly addressing candidates' inquiries.

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2.1.2 Employee Monitoring

As a result of the incorporation of artificial intelligence into the human resource department, it is now necessary for employees to possess the necessary skill set. According to Jain S. (2017), the majority of the time, it is challenging for employees to adopt and learn the artificial intelligence tools, as well as to reach a proficient level in the field of digital technologies. One of the most important aspects of any business is its human resources, and the implementation of an AI system may have an effect on the various levels of management, which will result in employees feeling more confident in their work. It can be challenging for the human resources department to find the right candidate to handle artificial intelligence tools, which is one of the core challenges facing the industry. As technology continues to supplant the authority and role of human resources in the decision-making process within an organization, one additional limitation and challenge is the restriction of the HR department's ability to make decisions in day-to-day life.

2.1.3 Internal Mobility

The implementation of AI has revolutionized the process, rendering it intelligent, optimized, self-reactive, effective, efficient, and automated, thereby eliminating numerous tasks that were formerly conducted manually, on paper, and necessitated substantial resources. AI deployment frequently encompasses the entire organizational value chain due to its efficiency and quality in innovation: research and development, maintenance, operations, sales and marketing, planning and production, demand forecasting, and services. Our existing notions regarding the support of decision-making by intelligent systems do not necessarily correspond with the capabilities of emerging AI systems (Paul et al., 2022). This special issue's articles, along with evidence from additional research, demonstrate that numerous workers, especially knowledge workers, are not readily substitutable by intelligent technologies. Nonetheless, their responsibilities and contributions may evolve as AI assumes specific aspects of their tasks: the incorporation of AI systems may require new delineations of labour between the employee and the intelligent system. This necessitates a distinct framework for understanding new relationships and the allocation of tasks, such as the notion of "supermind," which more adeptly acknowledges the potential contributions of AI agents as collaborators (Malone, 2018). We advocate for future research on AI that employs established sociological, psychological, and organizational theories to assess their relevance to AI systems in the workplace.

2.2 Artificial Intelligence

Knowledge management aligns with the AI community's objective—advancing and utilizing computational technology to enhance the efficacy of individuals and communities. Knowledge management requires artificial intelligence. The concepts and technologies developed by the AI community are essential for effective knowledge management, such as a knowledge base. Various terms may be employed, such as corporate memory, knowledge repository, and best-practices database; however, it is evident that a high-quality knowledge

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base is essential for effective knowledge management. A considerable body of previous research has concentrated on the challenges posed by AI to HRM, particularly regarding job displacement (e.g. Coupe, 2019; Ivanov and Webster, 2019; Arslan et al., 2021), evolving professional requirements (e.g. Hmoud and Lszlo, 2019), the necessity for new skill acquisition (Malik et al., 2020; Arslan et al., 2021), and the dynamics of talent management (e.g. Vrontis et al., 2021). KPMG's recent report indicates that most CEOs believe AI will generate more jobs than it will displace, whereas the majority of HR managers hold an opposing view (KPMG, 2019, p. 1). A primary reason for this disparity in perceptions regarding the role of AI is that, historically, the HR function within organizations has approached technologies, including AI, from a functional standpoint, emphasizing retraining and skills development for employees whose positions may be supplanted by AI. Nonetheless, the ongoing interaction between AI-driven robots and human employees in routine organizational tasks (e.g., Libert et al., 2020) remains a dynamic that has not been thoroughly examined by researchers or comprehensively understood by modern HR managers. It has been contended that the technologies linked to Industry 4.0 enhance the visibility of interactions and collaborations between humans and AI, typically manifested through robots, although other intelligent machines are increasingly apparent to augment productivity. This evolution introduces distinct challenges related to control, analysis, and performance assessment (e.g., Tsarouchi et al., 2017; Libert et al., 2020).

2.3 Workplace

Artificial intelligence is progressively being integrated into electronic markets, leading to widespread adoption among organizations across various industries and reshaping the global economy (Adam et al., 2020; Guan et al., 2020; Thiebes et al., 2020). Consequently, AI is regarded as a fundamental component of business strategy and organizational decision-making (Cheng et al., 2020a, b; Shrestha et al., 2019), thereby establishing it as a crucial factor in creating business value (Dwivedi et al., 2019). AI, as a pervasive concept (Siau & Wang, 2018), encompasses various subfields and dimensions (i.e., human-like thinking, rational thinking, human-like action, and rational action) (Russell & Norvig, 2016), yet it has not developed a coherent definition (Duan et al., 2019). Artificial intelligence is commonly linked to human intelligence; however, society is confronted with the question of how machines can attain such intelligent behavior (Neuhofer et al., 2020), resulting in a three-dimensional classification: narrow AI, general AI, and superintelligence (Batin & Turchin, 2017). Narrow AI encompasses self-learning methodologies that surpass human performance in particular, specialized tasks. General AI elucidates self-learning akin to human intelligence. Superintelligence, in theory, is believed to surpass human capabilities in every regard. Most implemented systems within organizations are classified as narrow AI, as they concentrate on specific work-related tasks (Batin & Turchin, 2017). Artificial intelligence is anticipated to fundamentally transform the workplace and work methodologies (Bednar & Welch, 2020), permeating various industries (Wang & Siau, 2019) with prospective applications in nearly every domain (Barredo Arrieta et al., 2020).

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2.4 Research Gap

Replacement view studies of AI's effects on employment depend on experts to evaluate the technology's prospective influence; however, we can investigate historical periods to verify its actual impact. The impact of technology on employment has been a persistent concern. Although technology has traditionally been viewed as a pivotal catalyst for societal transformation, analyses of critical industrialization epochs indicate that the implementation of essential technologies required years to influence economic growth and productivity (Brynjolfsson and Hitt, 1996; Brynjolfsson et al., 2017; David, 1989). This is partly attributable to the time required for companies to undergo organizational transformation to leverage the technology. In numerous manufacturing sectors that experienced substantial automation in the 1980s, innovations like flexible manufacturing systems and computer-integrated manufacturing transformed both methodologies and competencies. Manufacturing employment evolved into a combination of high and low-skilled positions, resulting in the elimination of numerous low-skilled (predominantly manual) roles. To comprehend the influence of AI, it is essential to examine it within the evolving intricacies of automation and labor. A significant portion of contemporary business operations resides in what Brian Arthur termed "the second economy": an economy characterized by "machines" that autonomously exchange and transform information, facilitating seamless, instantaneous, and thus "frictionless" transactions (Arthur, 2011). The essential components of this coordinated effort are the software and algorithms that transform work processes into data and information streams. Artificial intelligence further enhances this automation. We utilize instances of digitally transformed companies such as Amazon and Tesla to illustrate the impact of AI-enhanced automation on human labor, and examples like Netflix and AT&T to demonstrate how machines (i.e., AI and automation) have generated new functionalities that surpass human capabilities, thereby enhancing the overall productivity of these firms. A digital workplace allows employees to perform tasks, exchange information, and collaborate with team members both within the organization and with partner organizations, all without regard to geographical location for all involved parties.

3. Theoretical and Conceptual Framework

3.1 Relationship Between HRM Practices and Integration of AI

Human beings have consistently developed and utilized technology to enhance their capabilities beyond what is achievable without such tools. Neanderthals developed the earliest tools from stone and bone to facilitate food acquisition. Despite its advanced sophistication, AI is a human-engineered instrument conceived to enhance performance beyond what is achievable without it. The effects may vary depending on the stakeholders considered (Ekbia and Nardi, 2014) and the chosen perspective—micro, meso, or macro level. Outcomes also vary depending on the evaluation period. The implementation of AI technology may enhance efficiency regarding time and financial resources, primarily reflecting employer interests; however, the potential adverse effects on employees due to

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labor substitution cannot be disregarded, particularly at the local level in the short term. This is presently the situation regarding the integration of AI in logistics. Adopting a long-term perspective and prioritizing other stakeholders may result in a markedly different assessment of the same practice, particularly regarding environmental protection and overall societal welfare. Determining the augmentation potential of AI for human capabilities in the workplace hinges not on time and financial resources, but rather on criteria such as quality, precision, accuracy, health, safety, and motivation, which signify improved working conditions (Fischer, 2018; Markoff, 2016).

3.2 Relationship Between AI and the Transformation of the Workplace

Digital technologies are revolutionizing industries, products, processes, and operations. The workplace dynamics are evolving in organizations utilizing modern technologies like embedded systems and the Internet of Things (IoT). The dependence on technology for management functions such as planning, monitoring, implementing, and auditing has resulted in evolving interfaces for connecting individuals and managing tasks. The ubiquitous nature of work indicates that the workforce is predominantly interconnected through computers, mobile devices, and tablets, rather than through in-person interactions (Bolatet al., 2016). The term "digital world" initially encompassed technologies related to social media, mobile devices, analytics, and cloud computing. It now additionally includes cognitive computing and artificial intelligence (AI). Employees at digital workplaces anticipate the automation of all routine processes, incorporating integrated AI (Shivakumar, 2020). The demand for convenience, accessibility, and usability is propelling systems and processes within organizations, resulting in concomitant challenges related to data privacy and security. Technology serves as a facilitator in the workplace while simultaneously introducing new challenges. The sector Developments in 4.0 have significantly transformed workplaces. Flexible and agile work environments have arisen, integrating physical and digital dimensions of work. This has engendered new challenges for organizational structure and leadership. In the case of virtual global teams that are not colocated, individual contributions are not physically observable by colleagues or supervisors. The focus is on individual and team outputs rather than efforts. Consequently, performance metrics and workplace incentives have increasingly prioritized output, neglecting the recognition of effort. Virtual teams tend to experience a higher failure rate than success due to the inherent challenges of management (Colabi and Zarei, 2014).

3.3 Relationship Between HRM Practices and Transformation of Workplace

The expectations of modern employees in a mobile-connected and dynamic work environment pose numerous challenges for supervisors and the organization. A significant challenge pertains to the safeguarding of data, specifically regarding intellectual properties, trade secrets, organizational research and development efforts, and ongoing projects (Zekos, 2003). Organizations face the challenge of balancing local, global, and interorganizational system linkages while managing the distribution and reach of their products across diverse markets, vendors, and suppliers (Daniel and White, 2005). Overseeing a flexible, virtual, and

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dynamic workforce presents challenges in task allocation and oversight, administration of compensation and benefits, and execution of learning and development programs. Employees in the digital realm anticipate self-service applications for all services; additionally, they expect these applications to be readily accessible, user-friendly, and efficient (Jarvenpaa and Ives, 1994). The employee anticipates an amalgamation of work and personal identities, and the extent of alignment between these identities affects the employee's relationship with the organization (Ramarajan and Reid, 2013). Formulating curriculum for industry. The data-driven world is compelling organizations to adopt increased transparency, enhanced talent mobility, and improved management of data and technology. Leaders are anticipated to foster increased trust within the workplace, establish a flexible work environment, and safeguard intellectual property. The new leader is anticipated to exhibit greater agility, data-driven decision-making, transparency, global perspective, innovation, and collaboration compared to her predecessors from a decade ago (Kiron et al., 2016).

3.4 Research Framework

In the past year, numerous reports indicate the integration of AI into professional and business services organizations, with many developments reflecting and extending foundational AI research previously mentioned. In December, it was reported that the hedge fund managers at Bridgewater Associates were creating software to automate essential aspects of the firm's operations, including recruitment and strategic decision-making. The project is directed by David Ferrucci, who formerly oversaw the creation of IBM's Watson (Solon, 2016). In May 2016, the law firm Baker & Hostetler announced its intention to utilize the ROSS system, created by ROSS Intelligence (Turner, 2016). According to Gartner's prominent hype cycle (2016), machine learning is presently at the zenith of inflated expectations; inevitably, a trough of disillusionment looms as companies recognize that their aspirations significantly surpass current realities.

Although methodologies derived from AI research are beginning to permeate actual business services and professional procedures, their integration remains constrained in both magnitude and breadth. Artificial intelligence is predominantly utilized in environments that are extensively automated and reliant on digital technologies. The ambiguous essence of numerous commercial practices, particularly the pivotal function of human relationships in cultivating and advancing business connections, currently remains resistant to AI. Consequently, it is reassuring that AI presently lacks the ability to replicate the interpersonal skills essential for professional practice. This, however, may provide a deceptive sense of reassurance. The discourse regarding the influence of automation and AI on professional occupations typically begins with the premise that technology will eventually replicate and supplant existing roles, functions, and tasks, especially those that are the most routine or mundane in professional practice. This represents the automated supermarket checkout model of automation: The organization delegates a crucial function (grocery checkout) to largely autonomous technology (the automated till), thereby liberating staff time to address more complex, unusual, or challenging situations and tasks. The technology is integrated into

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existing processes, thereby reducing certain staffing expenses. This gives rise to the apprehension that our employment may be supplanted by automation.

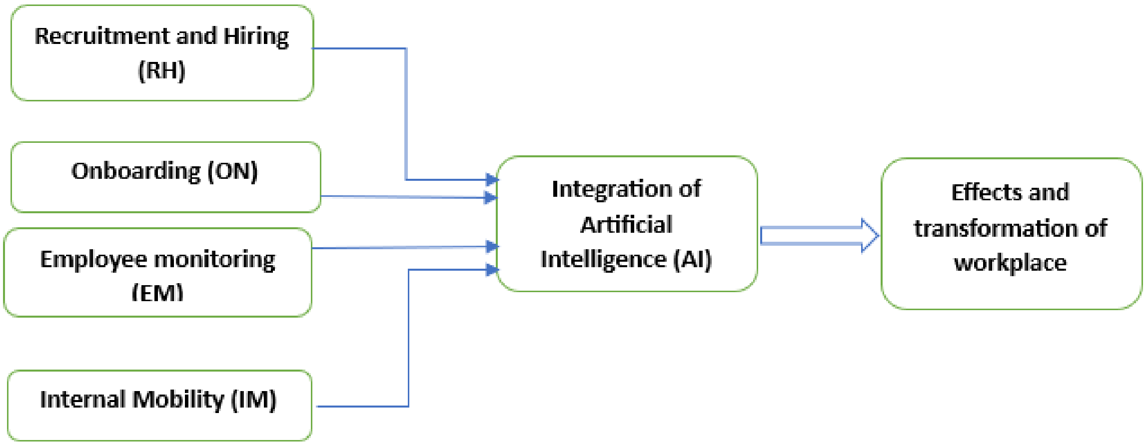

Figure1. Research Framework

1. Methodology

As the study is concerned with the workplace transformation through integration of AI, so professional and jobholders are selected as respondents for the survey.
The data was gathered through a standardized, non-comparative questionnaire employing a five-point Likert scale from "Strongly Disagree" (1) to "Strongly Agree" (5) to assess effects and transformation of the workplace. Two hundred ninety questionnaires were disseminated to individuals with business or financial expertise, resulting in 252 fully completed and usable responses, which corresponds to a response rate of 86.89%.

To ascertain that the sample size of 252 is sufficient and representative of the larger population, a theoretical formula must be employed to validate the sample's statistical integrity. In the absence of such validation, the reliability of the results may be called into question. Consequently, the authors must elucidate the methodology employed to ascertain the sample size, ensuring its adequacy for generalization

Before distributing the final survey, the questionnaire underwent pre-testing with a small cohort of five respondents to assess clarity, relevance, and efficacy in obtaining the intended information. Pre-testing is a crucial phase for identifying ambiguities or issues in the questions that may impact the quality of the responses.

4. Analysis and Discussion

4.1 Descriptive Statistics

The combined analysis of gender and age distribution in the sample (N=231) provides a complete picture of the demographic composition. The gender distribution shows a modest skew towards one group, most likely males, with a mean of 1.329 and a standard deviation of

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0.47087, indicating moderate variability (Table 1). The skewness is corroborated by a positive skewness value of 0.733. Meanwhile, the age distribution reveals a concentration of younger people, with a mean age of 1.7965 and a positive skewness value of 1.273. The standard deviation of 1.07022 indicates a wide age range, whereas the kurtosis of 0.691 supports a leptokurtic distribution. Understanding these demographic aspects is critical for determining how various groups will interact with and adapt to AI technologies in the workplace.

Table 1: Basic Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Gender	231	1	2	1.329	0.47087	0.733	0.16	-1.476	0.319
Age	231	1	5	1.7965	1.07022	1.273	0.16	0.691	0.319
Valid N (listwise)	231								

4.2 Assessment of Measurement Model

The assessment of the measurement model starts with the checking of indicator reliability. According to Hair et al. (2022), the threshold value for indicator reliability is 0.708. Outer loading values of all the items were above 0.708 except AI1 (0.690), AI4 (0.698), EM1 (0.679), IM1 (0.690), and TW2 (0.687). According to Hair et al. (2013), any weaker loadings between 0.40 and 0.708 can be removed if it increases construct reliability and validity. That is why these items were not removed, as removing them would not bring any major impact on the reliability and validity of the measurement model. The following table shows the outer loadings of the constructs (Table 2):

Table 2: Outer Loadings

	AI	EM	IM	ON	RH	TW
AI1	0.69					
AI2	0.789					
AI3	0.774					
AI4	0.698					
EM1		0.679				
EM2		0.813				
EM3		0.746				
IM1			0.69			
IM2			0.81			
IM3			0.765			
ON1				0.855		
ON2				0.844		
RH1					0.725	
RH2					0.766	
RH3					0.701	
TW1						0.775
TW2						0.687
TW4						0.762

Source: Smart-PLS Result Analysis

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Another tool of measurement model assessment is the checking the validity of internal consistency which is done through the assessment of Cronbach's alpha and composite reliability (Hair et al., 2019). Now the assessment of convergent validity (AVE) where is the acceptable range is 0.50. The construct reliability and validity of the model is given below:

Table3 : Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI	0.722	0.727	0.827	0.546
EM	0.603	0.61	0.791	0.559
IM	0.623	0.631	0.8	0.572
ON	0.616	0.616	0.839	0.722
RH	0.563	0.564	0.775	0.534
TW	0.591	0.592	0.786	0.551

The Cronbach's alpha for AI, EM, IM and ON is above 0.600 (0.603-0.780) (Table 3). According to Hair et al., (2022) the threshold value of Cronbach's alpha is 0.70 although Raharjanti et al., (2022) indicates that Cronbach's alpha value of 0.60 to 0.80 is also acceptable. The Cronbach's For RH and TW is above 0.50 but lower than 0.60. According to Taber, (2018) alpha values were categorized as excellent (0.93-0.94), strong (0.91-0.93), reliable (0.84-0.90), robust (0.81), fairly high (0.76-0.95), high (0.73-0.95), good (0.71-0.91), relatively high (0.70-0.77), slightly low (0.68), reasonable (0.67-0.87), adequate (0.64-0.85), moderate (0.61-0.65), satisfactory (0.58-0.97), acceptable (0.45-0.98), sufficient (0.45-0.96), not satisfactory (0.4-0.55), and low (0.11). The range used by scholars is arbitrary, with no obvious hierarchy (e.g., "high" vs. "fairly high," "not satisfactory" overlapping with "sufficient" or "acceptable"). According to Schmitt, (1996), instruments with low alpha values can still be effective in certain situations, given there is no universally accepted level (e.g., 0.70) which was further supported by Plummer & Ozcelik, (2015). This study tries to find the influence of artificial intelligence among workplace. The two constructs RH (recruitment and hiring) and TW (effects of transformation of workplace) significantly contribute to this study. Although the Cronbach alpha of these two constructs are between 0.50 and 0.60 but can be deleted as it has significant contribution in workplace development which is similar to the study by Griethuijsen et al., (2015). In their study two of the major constructs with lower Cronbach alpha were not deleted considering its contribution to the study. This study, the reliability value for each of the construct is minimum 0.80 although according to Hair et al., (2019) the composite reliability is considered to be more reliable. So, AVE (Average Variance Extracted) assessment is considered the convergent validity assessment where the threshold value is minimum 0.50. For this study, the AVE of all the construct is above 0.50 (0.534-0.722).

The assessment of discriminant validity is another requirement after the assessment of construct reliability and validity. One of the traditional way of assessing discriminant validity is use of Fornell and Larker method. According to Fornell & Larcker, (1981) each construct's squared inter-construct correlation with every other reflectively evaluated construct in the structural model should be compared to its own AVE. Moreover, another way of assessing

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discriminant validity is the assessment of cross loadings. The Fornell and Larcker indicates good discriminant validity (Table 4). The results of the Fornell and Larcker shows good discriminant validity as most of the √AVE values are greater than corresponding correlations (Cheung et al., 2024). The cross loadings for assessing of discriminant validity is recommended by Henseler et al., (2015) where they mentioned that almost most of the PLS tutorial articles and introductory books advise applying the (Fornell & Larcker, 1981) and cross loadings (Chin, 1998). In order to measure discriminant validity, the cross loadings of each item on various variables were examined. Each item loads the most on its intended construct. For example, AI1 loads 0.69 on AI, which is higher than its loadings on EM (0.533), IM (0.399), ON (0.352), RH (0.445), and TW (0.363). This trend is consistent across all items, showing strong discriminant validity. The Fornell and Larcker and Cross Loadings are shown in the following Table 5:

Table 4 : Fornell and Larcker

	AI	EM	IM	ON	RH	TW
AI	0.739					
EM	0.655	0.748				
IM	0.677	0.606	0.756			
ON	0.608	0.469	0.553	0.85		
RH	0.63	0.696	0.588	0.501	0.731	
TW	0.654	0.593	0.595	0.604	0.634	0.743

Table 5: Cross Loadings

	AI	EM	IM	ON	RH	TW
AI1	0.69	0.533	0.399	0.352	0.445	0.363
AI2	0.789	0.493	0.488	0.421	0.491	0.539
AI3	0.774	0.512	0.524	0.461	0.438	0.531
AI4	0.698	0.412	0.575	0.548	0.488	0.479
EM1	0.442	0.679	0.34	0.256	0.364	0.3
EM2	0.511	0.813	0.531	0.469	0.593	0.49
EM3	0.513	0.746	0.475	0.315	0.585	0.524
IM1	0.473	0.363	0.69	0.426	0.346	0.369
IM2	0.552	0.547	0.81	0.443	0.463	0.488
IM3	0.509	0.453	0.765	0.386	0.519	0.486
ON1	0.526	0.419	0.521	0.855	0.482	0.521
ON2	0.508	0.377	0.417	0.844	0.368	0.505
RH1	0.453	0.586	0.431	0.415	0.725	0.491
RH2	0.474	0.516	0.364	0.279	0.766	0.473
RH3	0.455	0.424	0.496	0.41	0.701	0.426
TW1	0.504	0.445	0.404	0.446	0.43	0.775
TW2	0.481	0.464	0.47	0.485	0.484	0.687
TW4	0.471	0.41	0.452	0.412	0.499	0.762

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4.3 Assessment of structural model

The structural model needs to be assessed after the assessment of the measurement model. According to Hair et al., (2022) collinearity is required to assessed which has to be less than 5. Any value above 5 would be considered as collinearity. According to Becker et al., (2015) VIF value between 3-5 considered lower collinearity whereas value less than 3 is considered no collinearity suggested by Hair et al., (2019). The VIF value of all the items are between 1.10 and 1.75 which indicates no collinearity exists. All the VIF values are shown in the following Table 6:

Table 6: VIF

	VIF
AI1	1.316
AI2	1.536
AI3	1.473
AI4	1.233
EM1	1.174
EM2	1.357
EM3	1.215
IM1	1.156
IM2	1.337
IM3	1.282
ON1	1.247
ON2	1.247
RH1	1.172
RH2	1.216
RH3	1.126
TW1	1.274
TW2	1.111
TW4	1.281

The verification of R^2 value would be helpful to know the explanatory power of the model. According to Shmueli et al., (2019) the R^2 value of 0.75, 0.50 and 0.25 is considered as substantial, moderate and weak. The R^2 value of TW is 0.428 which indicates that the model has 42.8% of explanatory power of the variance of the dependent variables (Table 7).

Table 7: Performance using R Square

	R-square	R-square adjusted
AI	0.615	0.608
TW	0.428	0.426

Source: Smart PLS Result Analysis

The assessment of P-value is required after the R^2 value of the study is determined. According to Hair et al., (2019) the acceptance or rejection of the hypothesis is determined by the P-value which has to be less than 0.05 to be accepted (Table 8) (Fig. 2).

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Table 8: Path Coefficient Values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AI -> TW	0.654	0.66	0.042	15.471	0
EM -> AI	0.25	0.251	0.081	3.086	0.002
IM -> AI	0.296	0.298	0.07	4.259	0
ON -> AI	0.248	0.251	0.061	4.101	0
RH -> AI	0.158	0.158	0.083	1.906	0.057

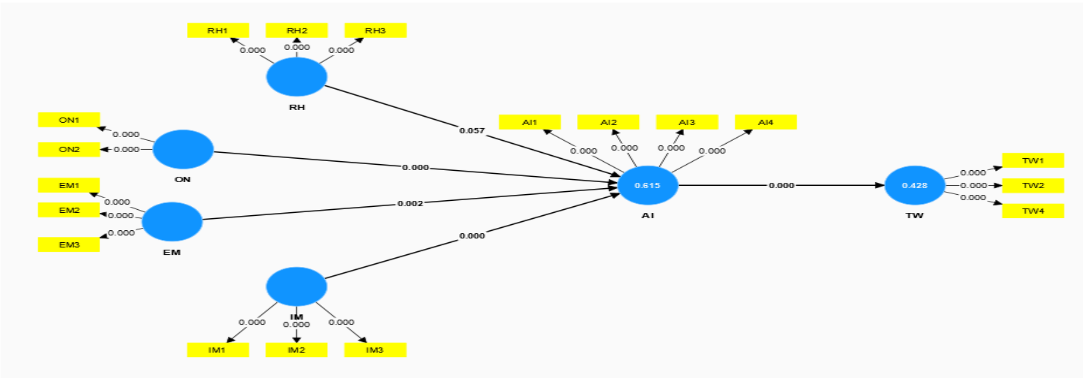

Figure 2: Structural Model

The above table shows that four of the hypotheses H2, H3, H4 and H5 are accepted except H1 which fails to accept.

4.4 Robustness Tests

4.4.1 Assessment of Nonlinear Effects

So, the verification of quadratic effect to check for nonlinearities. The outcome of bootstrapping with 10000 samples indicate that all the quadratic effects were insignificant (p>0.05). so, we can conclude that the linear effects of the model is robust (Sarstedt et al., 2020) which are shown in the following Table 9:

Table 9: Path Coefficient Results

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
QE (RH) -> AI	-0.004	-0.006	0.047	0.088	0.93
QE (ON) -> AI	0.038	0.038	0.042	0.896	0.37
QE (EM) -> AI	0.042	0.04	0.043	0.968	0.333
QE (IM) -> AI	-0.068	-0.066	0.037	1.823	0.068
QE (AI) -> TW	-0.022	-0.017	0.041	0.535	0.592

4.4.2 Assessment of Endogeneity

Furthermore, this study completed the assessment of potential endogeneity using Gaussian copula method. Two types of relationships were tested which are single relationship and double relationship (Table 10 and 11). The outcome indicates all insignificant relationships (p>0.05) of the gaussian copula which ensures no issues on endogeneity ensuring the robustness of the structural model for single and double relationships. So, it can be said that

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endogeneity is not found in this study which supports the robustness of the structural model (Hult et al., 2018).

Table 10: Gaussian Copula (Single Relationship)

Single Relationship					
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
GC (RH) -> AI	-0.085	-0.069	0.25	0.339	0.735
GC (ON) -> AI	-0.15	-0.126	0.108	1.385	0.166
GC (EM) -> AI	0.041	0.12	0.188	0.216	0.829
GC (IM) -> AI	-0.262	-0.21	0.142	1.845	0.065

Table 11: Gaussian Copula (Double Relationship)

Double Relationship					
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
GC (RH) -> AI	-0.085	-0.069	0.25	0.339	0.735
GC (AI) -> TW	-0.017	0.003	0.205	0.082	0.934
GC (ON) -> AI	-0.15	-0.126	0.108	1.385	0.166
GC (AI) -> TW	-0.017	0.003	0.205	0.082	0.934
GC (EM) -> AI	0.041	0.12	0.188	0.216	0.829
GC (AI) -> TW	-0.017	0.003	0.205	0.082	0.934
GC (IM) -> AI	-0.262	-0.21	0.142	1.845	0.065
GC (AI) -> TW	-0.017	0.003	0.205	0.082	0.934

4.2.3 Assessment of Unobserved Heterogeneity

FIMIX-PLS procedure was used to assess the unobserved heterogeneity of the PLS path model (Table 12). For, determining maximum number of segments, the minimum number of sample size required to estimate each segment was calculated suggested by (Hair et al., 2019; Vaithilingam et al., 2024). The maximum number of iterations (5000) and the number of repetitions (10) was used after the calculation of segments. Moreover, A post-hoc power analysis using an effect size of 0.15 and an 80% power level indicates that a minimum sample size of 85 is needed to extract up to five segments. We use FIMIX-PLS for three segments with the same settings as the initial analysis (Vaithilingam et al., 2024; Sarstedt et al., 2020). Our total sample size is 231, so the total number of segments for this study was 3. FIMIX-PLS was run for one to three segments and the outcome is given belo:

Table 12: Assessment of Unobserved Heterogeneity

	1	2	3
AIC3 (modified AIC with Factor 3)	982.64	946.46	**933.787**
CAIC (consistent AIC)	1006.737	**998.096**	1012.962
AIC4 (modified AIC with Factor 4)	989.64	961.46	**956.787**
BIC (Bayesian information criterion)	999.737	**983.096**	989.962
MDL5 (minimum description length with factor 5)	**1152.125**	1309.641	1490.665
EN (normed entropy statistic)	0	0.36	0.577

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Three segments solution has been found in AIC_3 whereas CAIC identified two segments' solutions. However, the minimum description length with factor $_5$ is one segment solution. All together these analysis does not unambiguously show a specific segmentation, because (1) AIC_3 and CAIC show different segments and (2) AIC_4, BIC and MDL_5 also indicates to different segments. So, unobserved heterogeneity is not found at a critical level. So, based on the robustness checks, we can consider that this model is robust.

4.4 Discussion

The findings of this study give insights into how AI-driven HRM practices contribute to workplace transformation. First, we found that there is no link between recruitment and hiring and AI integration. This could be because organizations do not fully trust AI in making hiring decisions. They may be worried about algorithms, lack of transparency or not having enough expertise. Also most respondents were professionals and their limited involvement in strategic HR decisions may have affected this outcome. On the hand employee monitoring, onboarding and internal mobility showed significant positive effects on AI integration. This means that AI is easily accepted in operational and administrative HR functions where efficiency gains are immediate and measurable. AI-powered monitoring systems improve performance tracking and productivity insights. Onboarding tools make employee integration and training processes smoother. AI-driven internal mobility systems enable talent allocation through data-driven decision-making.

AI facilitates automation improves decision accuracy and supports analytics. This enables organizations to transition toward agile data-driven and digitally connected work environments. Another key observation is that younger employees are more adaptable to AI tools. Older employees may experience productivity gains. This suggests the need for targeted training and reskilling initiatives to bridge the divide within organizations. Overall the results support the idea that AI augments capabilities rather, than replacing them. The research provides evidence that AI mainly enhances HR functions than fully automating them. It also highlights the importance of factors like age and skill level in determining the success of AI adoption (table 13).

Table 13: Summary of Hypotheses results

H1: Recruitment and hiring positively influence the integration of artificial intelligence	Not Accepted
H2: Onboarding positively influences the integration of artificial intelligence	Accepted
H3: Employee monitoring positively influences the integration of artificial intelligence	Accepted
H4: Internal mobility positively influences the integration of artificial	Accepted

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intelligence	
H5: Integration of artificial intelligence positively influences the transformation of the workplace	Accepted

5. Conclusion

Therefore, with notable advancements in fields including human resource management (HRM), the integration of artificial intelligence into business and professional services is moving constantly forward. Though artificial intelligence is becoming more and more common in the workplace, several elements still limit its complete acceptance and integration, including the complicated, relationship-driven character of many professional roles. The research framework reveals that although artificial intelligence shows promise in areas including employee monitoring, onboarding, and internal mobility, its influence on recruitment and hiring is less conclusive, mostly due to generational and skill-based variations among employees. Moreover, artificial intelligence clearly changes the workplace, especially in terms of organizational efficiency enhancement and decision-making support. Nevertheless, the discrepancy between the ambitions of artificial intelligence in business processes and the present technological constraints emphasizes the need of creating strategic frameworks to direct AI acceptance. The future success of artificial intelligence will depend on its ability to solve problems and guarantee flawless integration into corporate cultures as it keeps changing HRM and professional standards.

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