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A Study on the Implications of AI on Industry 4.0: Digitalisation of Human Resources

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ABSTRACT

Robotics innovation, encompassing the Internet of Things and AI, has created vast scenarios in the workplace. Flexibility, precision, and efficiency are some of Industry 4.0's possible advantages. Industry 4.0 deployment calls for several adjustments, encompassing the Human Resources (HR) department. The HR department's skills are crucial in Industry 4.0 and provide an advantage for the company, more caution and flexibility in the HR department's capacity to respond to the necessities and challenges. We explore the role of AI in the digitalization of HR and practices associated with Industry 4.0. A total of 258 HR experts from administration, manufacturing, and information technology (IT) were chosen to take part in this evaluation, which investigated three aspects of HR readiness and five AI applications in HR operations. The collected data were analyzed using the Statistical Package for Social Sciences (SPSS) software along with Analysis of Moment Structures (AMOS). The findings suggested that a key factor in achieving sustainable development is the analysis of hierarchical structures. The five components of AI application areas in HR all improve the abilities and adaptability of human resources. Enhancing safety and well-being was also considered essential for AI integration in HR.

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1. Introduction

According to Gartner (2024), AI is increasingly integrated into organisations, especially in human resource management (HRM). AI's role in HR has grown significantly, acting as a bridge between people and technology in the Industry 4.0 era. Although technology is automating numerous conventional HR tasks, the need for adaptable, responsive HR services is growing. Technology can enhance agility in HR by streamlining processes and enabling quick adaptation to change. Gartner (2024) states that almost three-quarters of HR leaders are sure that the inability to implement AI in the next two years will have a negative impact on organisational performance, explaining the urgency of digital transformation in HR. Likewise, according to Deloitte (2024), Global GenAI in Business Report, more than 60 percent of businesses have already implemented AI-based solutions in various business units, which proves that AI has become the focus of business strategies. The example of leading technology companies like Facebook, Google, Amazon, Apple, and Microsoft is no exception as they incorporate agile HR and AI-enabled practices to remain responsive and competitive in the Industry 4.0 era. The ability of the human resources division to promptly adjust and react to shifts in market conditions, business requirements, and technological breakthroughs is known as HR agility. Flexibility in HR approaches, the application of AI, and other technologies to enhance decision-making and automate tasks, along with the quick addressing of emerging challenges, such as employee disengagement or skills shortages, make up every element of it. Agile HR employs techniques such as design thinking to ensure that solutions align with the goals of the organization and the needs of employees. This keeps the HR department aligned with the evolving requirements of the company.

Despite AI’s rise, HR’s core goals—recruitment, training, and the retention of skilled employees remain unchanged (Chan, 2024). HR agility involves supporting people and organisational strategies through adaptive processes. Agile HR practices improve employee engagement and are particularly useful in dynamic environments lacking standardisation. However, HR often faces criticism for slow responses, which can affect employee satisfaction. To remain competitive and attract talent, businesses must support HR in adapting to technological changes. Agile HR comprises: (1) fast identification of problems, (2) shortening the response time, and (3) applying design thinking to effective planning (Wang, 2019; Yang et al., 2021). HR processes that are transformed with the help of AI encompass payroll, health and safety, real-time feedback, and employee productivity (Murugesan et al., 2023). The awareness of the role of AI in these processes assists organisations in optimising efficiency by analysing and designing the organisational network.

This paper examines the ways in which HR digitisation is either a myth or a reality in enhancing productivity (Sharma et al., 2023). AI assists in monotonous HR activities, such as job advertisement and screening of candidates (Mer, 2024). It can detect the lack of skills and suggest upskilling or recruiting strategies. AI is also useful in personalizing employee development, as it monitors performance and learning trends (Dima et al. 2024).

However, challenges remain. The risks associated with AI implementation are the privacy of data and model transparency (Mer, 2024; Saraswathi et al., 2023). The lack of alignment in technology strategies is also a problem in terms of cost-effectiveness (Dima et al. 2024). AI in HR presents pros on speed and predictive capabilities, especially in assessing emotional job performance, while posing severe issues about privacy and decision-making for employees. Sensors and AI-powered cameras could possibly infringe upon the privacy rights of employees since these cameras would keep recording the actions and emotions of them. The opportunity for taking shortcuts will arise through data breaches and avenues will be created for reckless surveillance. Moreover, AI might make performance assessments more objective or discriminatory if algorithms are trained with the wrong data, thereby adding to the workplace inequalities already present. AI decisions might skip information that human expertise might normally detect, such as interpersonal conflicts or external factors. Hence, AI can improve HR operations, but it must be assisted by human interaction, especially where emotional well-being is at stake due to the need for understanding and empathy. These will ensure that the data use is transparent, become ethically bound, and maintain the balance between human monitoring and automation for the empowerment of employees through AI.

This research aims to determine how AI in HR can boost productivity and clarify misconceptions about digitisation. It offers guidance for improving HR efficiency and effectiveness. The study focuses on two key HRM aspects: (i) AI application domains, and (ii) HR agility, derived from concept papers and articles.

To fill these gaps, this paper formulates a conceptual framework (Figure 1) that incorporates the major areas of AI implementation in HR, such as recruitment and onboarding, payroll automation, workplace decision-making, employee training, performance monitoring, and real-time feedback, and discusses their overall effects on HR agility in Industry 4.0. The framework, which is based on the previous literature as well as the empirical analysis, places AI as a strategic facilitator of HR flexibility, efficiency, and sustainability.

This work contributes to the current body of knowledge in a number of academic ways. First, it constructs and empirically proves a holistic conceptual framework, which combines the main AI applications with the human resource (HR) agility dimensions in the Industry 4.0 setting. Second, it offers empirical data that demystifies the myths versus the realities of AI-driven digital transformation of HR practices. Third, it builds on existing HRM literature by providing industry-specific knowledge on Indian industries, which are underrepresented in the current literature. Together, these contributions contribute to the theoretical knowledge and offer practical implications to HR professionals and policymakers who need to align AI adoption with organizational agility and sustainability objectives.

Research Questions:

- RQ1: How may AI affect HRM to meet Industry 4.0 needs?
- RQ2: How can AI support sustainability in Industry 4.0 HRM?

Research Objectives:

- RO1: Investigate recent developments in AI for HRM.
- RO2: Evaluate AI’s impact on HRM aligned with Industry 4.0.
- RO3: Examine AI’s role in promoting sustainability.

A conceptual framework is developed through literature review, offering actionable insights for stakeholders to address challenges in AI implementation.

2. Literature Review

Human resources functions have evolved and become increasingly dynamic (Singh et al., 2016). Studies show HR's effectiveness and the role of AI in enhancing agility in sectors like healthcare (Chowdhury et al., 2019). AI's primary feature is its ability to connect physical objects, e.g., pacemakers, vehicles, and displays, to the internet (Mohammed et al., 2022). The IoT enables sensing, processing, and the communication of real-world data, which is crucial for AI applications in HR. Sensors measure factors such as usage, temperature, speed, and faults, generating continuous and detailed data (Eleonora, 2014; Faria, 2010; Williams, 2015).

2-1. The Role of AI in HR Practices

AI's application in HR has expanded significantly (Chan, 2024). HRM involves recruiting, developing, and retaining employees to meet organisational goals. With Industry 4.0, there is an increasing demand for digital, automated, and flexible HR systems (Gartner, 2024). AI and the IoT enabled Industry 4.0, which transformed the HR function by automating traditional processes like hiring, payroll, and performance monitoring. HR took on a more adaptable role by utilizing AI to improve decision-making, expedite processes, and provide instant feedback, all of which increased overall responsiveness and productivity. AI-powered solutions also helped monitor worker productivity and well-being by evaluating comfort, safety, and health. Such insights had galvanized increased engagement and had avoided tiredness. However, the incorporation of such technologies wasn't without its snag, with algorithmic bias, data protection issues and potential job displacement being chief among them. For HR to prosper, ethical concerns, and technological developments needed to be made congruent to ensure fairness, transparency and business alignment.

AI enhances HR accuracy, efficiency, and decision-making. It significantly improves recruitment by automating resume screening and identifying top candidates (Mohammed et al., 2022). It also supports engagement and retention by detecting patterns that indicate low morale or high turnover, enabling proactive strategies. Artificial intelligence might very well improve human resource management; however, the list of concerns is long, the foremost being raised over the ability of this technology to increase existing biases. In various situations, AI systems trained on historically biased data maintain and promote inequality in areas such as promotions, hiring, and employee performance evaluations. Another key ethical concern is that human resource analysts may find it challenging to understand or justify an algorithmic outcome in an AI-facilitated decision-making process due to the lack of transparency. Other issues raised include the loss of jobs caused by automated HR processes as well as decision-making bereft of human empathy. Privacy becomes an issue when AI technologies, such as sensors and facial recognition, monitor employee behavior and mental health. The research proposes several mitigating suggestions to address these issues. This is because they include regular bias audits, incorporating worker feedback into AI systems, using inclusive and representative datasets, integrating AI tools with human oversight, ensuring algorithmic transparency via explainable AI, and following all legal standards and ethical frameworks.

Learning tools based on AI recognize skill deficiencies and prescribe specific training, customizing the content to the needs of employees. Within the framework of performance management, AI processes data to create personal improvement plans and monitor progress (Chan, 2024; Garima et al., 2020).

To ensure compliance and safety, AI uses sensor data to identify risks and propose preventive actions, minimizing accidents (Reddy et al., 2023). Moreover, from an HR perspective, the AI has the power to completely transform the way decisions are made in the areas of recruitment, training, performance management, and workplace safety, and in the way operations are conducted (Patel et al., 2018). Sareddy and Khan (2024) depict the practical implementation of AI via GNNs to address some of the most crucial issues in HR digitization. GNNs can improve talent mapping by clustering employees around skills and interactions, and can also make more accurate and personalized project recommendations, even with sparse data. That is precisely aligned with, or in essence, one of the goals pursued by Industry 4.0, which helps to promote data-driven HR practices and minimize manual decision-making. Additionally, the predictive capabilities of GNNs for career development and project outcomes showcase how AI can transform traditional HR systems into intelligent, adaptive frameworks. Consequently, the incorporation of GNNs demonstrates how AI enhances the effectiveness, customization, and tactical progress of human resource management in the digital age.

However, ethical concerns such as bias and job displacement—must be addressed. The effectiveness of AI in HR depends on balancing automation benefits with the need for human empathy and judgment.

While prior studies (Dima et al., 2024; Murugesan et al., 2023) demonstrate AI's potential in HR, the major part of such literature talks about specific applications (recruitment, payroll automation) and do not attempt to investigate the operationalizing effects with respect to HR agility and sustainability in Industry 4.0. This study fills that gap by developing and testing a complementary framework based on linking AI applications to HR agility outcomes.

Based on the previous literature reviewed, the present study integrates various theories for the development of a comprehensive conceptual framework explaining the relationship of AI-driven HR applications with HR agility in Industry 4.0. The framework illustrated in Figure 1 emphasizes key dimensions of HR using AI, i.e., recruitment, training, performance monitoring, and feedback, and how it all adds to the capacity of the organization to adapt and sustain itself. Essentially, this framework provides a theoretical basis for the empirical analysis presented in the later section.

2-2. Conceptual Framework

2-2-1. Embedding New Hires and Payroll Processing

According to Chan (2024), AI supports HR managers in identifying qualified candidates by leveraging machine learning to filter large applicant pools. Generative AI (GenAI) can draft job postings by extracting details about the role, company culture, values, and benefits. Additionally, AI automates administrative tasks like processing time-off requests, updating employee data, and calculating payroll and taxes (Mohammed et al., 2022). These features reduce errors and improve efficiency by identifying issues such as duplicate payments or incorrect tax calculations. AI also ensures compliance with payroll regulations, mitigating risks related to wage laws (Balsmeier et al., 2022).

AI can streamline onboarding by recommending tailored training or assigning a mentor based on prior experience (Chan, 2024). It can also personalise onboarding milestones (30/60/90-day plans), enhance engagement, and speeding up productivity while freeing HR to focus on human interaction.

2-2-2. Improvement at Workplace Decisions

AI helps detect and prevent workplace risks by analysing sensor and device data (Li et al., 2020). It can monitor employee health data for early signs of issues, providing personalised recommendations (Ngai et al., 2020). AI-powered chatbots offer real-time support on safety policies and assist in emergencies (Arias, 2021). Additionally, AI can enhance ergonomics by monitoring movement and identifying strain risks, leading to workstation adjustments and fewer injuries (Jerman et al., 2020; Subramaniam et al., 2021).

2-2-3. Enhancing Employee Performance and Comfort

Employee retention is higher for organisations that provide learning and skill development opportunities (Chan, 2024). AI may help with training and development by examining each employee's unique learning style and utilising that information to produce training materials and modify learning routes according to each person's success. Examining an employee's experiences, training, tenure, and performance data, such as objectives fulfilled and performance reviews received, may also create actionable guidance for goals and further steps and produce additional development ideas. Supporting employees' professional development may boost employee engagement and retention, while also making them feel appreciated, which may enhance worker comfort in several ways. HR departments can use AI for routine tasks, performance insights, and data analysis to increase efficiency while keeping a human touch. AI enables HR to concentrate on human-centered interactions by tracking employee sentiment, identifying disputes, and making learning recommendations. Human judgment is crucial for making final judgments, but AI also helps to reduce bias in hiring and promotions. This harmony between human interaction and AI-powered automation creates a positive, employee-centred atmosphere. To begin with, AI-driven systems can enhance the work environment, ensuring it is comfortable for staff by analyzing data from various sources, such as temperature sensors. For instance, based on the count of employees present at the job site, the system is able to adjust temperature and humidity settings (Zhang, 2021). Moreover, by providing tailored suggestions for employee comfort, AI will help customize the worker experience. AI-driven solutions, for example, can recommend modifications to workstations or chairs based on the worker's preferences and body shape (Yu, 2020). Third, AI would help recognize workplace stressors and provide recommendations for alleviating stress. AI-powered solutions can monitor data such as communication trends, employee engagement metrics, and various indicators to identify potential stressors in the work environment. This data can be utilized to implement actions that enhance employee comfort and reduce stress levels (Ugwu et al., 2020). AI has radically transformed HR processes to engage employees, train, and hire them. The automation of such processes as resume screening and shortlisting of candidates enhanced the efficiency and decision-making of the hiring process. The disengagement was early detected and treated, with an AI helping with individualized experiences and real-time feedback to employee engagement. The AI tracked skill growth during the training and adapted the development plan. Despite these benefits, other issues remained, such as job security, data privacy, and AI bias. Although AI enhanced HR agility and efficiency in general, its use had to be handled with care to avoid ethical standards and human judgment. The HR agility facilitated the HR departments to enact immediate adaptations to opportunities, challenges, and changes and thus, could give a higher satisfaction to employees and organizational performance in dynamic working environments. While Industry 4.0 advanced the warp and weft of the workplace due to rapid technological advancements, HR agility responded quickly to changing employee needs and market dynamics. It enhanced the decision-making process, working conditions, and operational efficiency in areas such as recruitment, payroll, and performance management. AI supports such agility by automating work, personalizing staff development, and providing real-time performance feedback. Predictive analytics also helped in retaining talents as they could identify at-risk workers early. AI made the work more efficient, yet, it also raised the question of data protection and equity, which HR had to address to retain the trust of employees. By integrating AI with agile methods, HR departments have ensured their responsiveness, ethics, and efficiency to ensure that they meet the needs of the company and its people in a constantly evolving environment.

2-2-4. Elevating Employee Productivity EEP

AI can assist in improving employee engagement by providing a personalised and responsive work environment. AI technologies may be used to construct personalised training plans for staff members based on data gathered about their objectives and the demands of the business. Furthermore, AI may be used to detect and track workforce trends, including the degree of employee involvement in corporate events and performance reviews. By keeping track of this information, your HR department will be able to predict disengagement and identify a solution in time, such as allowing managers and staff to have more in-depth discussions during performance reviews before disengaged workers decide to quit (Chan, 2024). HR personnel can focus on different facets of their roles by leveraging AI to automate tedious administrative tasks. As a result, HR personnel might increase their productivity, allowing for more time dedicated to tasks requiring their expertise (Czarnitzki et al., 2023). AI can help measure employee productivity in real time. To provide immediate feedback on worker productivity, AI-driven systems can analyze employee information, such as time dedicated to tasks and completion rates of assignments. Using this data, employee performance might be improved, and issues can be pinpointed (Bäck et al., 2022). AI can assist in more objectively measuring worker productivity. Subjective assessments and other traditional techniques of measuring employee productivity might be incorrect and biased (Strohmeier, 2020). By employing data and analytics to make well-informed judgements, AI-powered systems can offer more objective assessments of worker productivity (Chowdhury, 2020). Besides these AI applications, there are certain other applications of AI in HR that can significantly boost employee productivity: ensuring work comfort and performance, recruitment decision making, automating payroll and onboarding, real-time feedback, interaction, and work productivity. By automating repetitive operations, AI enabled objective performance appraisals, provided real-time feedback, and supported personalized training to improve employee productivity. The AI application improved comfort and performance, wherein development plans are tailored for the employee, work environments are adapted using sensor data, and stressor detection is carried out. It further tracked continuous feedback and delivered immediate, unbiased feedback that boosted participation and communication. AI-based workplace decision-making monitored health and safety risks, proposed ergonomic changes, and helped in emergencies. AI-based onboarding supported interactive onboarding with personalized onboarding plans, payroll management, and recruitment acceleration.

2-2-5. Employee Involvement and Real-Time Feedback

AI's ongoing ability to collect information can be leveraged to assemble management and peer reviews along with employee performance data throughout the entire year (Chan, 2024). AI can then utilize this information to generate a comprehensive summary of a person's work, acting as a basis for performance evaluations. Employing AI to aid in performance management activities can help curb the tendency to overvalue recent events. Managers may use GenAI to create an initial performance evaluation featuring bullet points about an employee's performance, which they can later review and adjust. This implies that managers could allocate more time engaging in significant discussions about tasks, actions, and accomplishments with staff and reduce time crafting the material for performance evaluations. AI-powered tools can assist in delivering prompt feedback to employees in multiple ways. Initially, AI can assist in tracking employee performance as it happens, offering insights on advancement and pinpointing aspects that need enhancement. Each employee can obtain this feedback customized to their individual needs, helping them improve their performance in particular aspects. Additionally, AI can assist in delivering more unbiased feedback. Personal assessments and conventional feedback approaches can be inconsistent and biased. The accuracy of the feedback given can be enhanced by utilizing AI-based systems to deliver more objective feedback based on data and analytics (Vrontis et al., 2022). Ultimately, AI can accelerate the process of providing feedback. AI-powered systems can deliver feedback instantly or almost instantly due to their rapid data processing capabilities, enabling employees to swiftly respond to enhance their performance (Durana et al., 2022).

2-2-6. Differentiate between Myth and Reality

Several HR processes, including recruitment, induction, performance appraisals, and employee engagement, might be automated by AI-based solutions. In order to reduce the effort and time spent on manual processing, AI can be used to automate the filtering and shortlisting of job applications (Nawaz, 2019; Sharma et al., 2022). Through the provision of personalized training and development programs, AI can also facilitate the automation of the recruitment process (Da Silva et al., 2022). AI can also help in real-time monitoring of employee performance, providing data-driven insights that can be utilized to improve employee engagement and performance management (Li et al., 2023). AI in HR has a role in digitisation that extends beyond the operational efficiency (Johansson & Herranen, 2019). Through the provision of fact-based information that can inform strategic decision-making, AI can also help improve the quality of HR decisions (Dolan et al., 2022). For instance, HR managers can develop targeted training and development plans to reskill employees by utilizing AI-based applications to identify talent gaps in the workforce (Joshi, 2020).

2-2-7. Determine the Potential of AI

Organisational Network Analysis (ONA) for data gathering and analysis may be automated with the use of AI-powered technologies. AI, for example, can identify the main opinion leaders and influencers in a company by analysing email conversation patterns (Ye et al., 2021). Additionally, AI can uncover informal networks within an organisation by analysing data from social media (Ye et al., 2020). Additionally, AI may examine survey data to determine the elements that affect worker collaboration and engagement (Sarkar & Maiti, 2020; Vishwakarma, 2023). Beyond data gathering and analysis, AI in HR influences ONA. AI may also be used to find and fix inefficiencies and gaps in networks. For example, HR managers might create focused interventions to enhance communication and cooperation by using AI-powered tools to detect communication breakdowns and bottlenecks (Yu et al., 2023)

2-2-8. Evaluate and Grade the Success Criteria

AI-enabled systems can help systematize the analysis of organizational design information. AI can, for example, assess data regarding experience, skills, and job performance to identify which candidates are best qualified for a specific role. To identify potential areas for talent enhancement, AI can also analyze information regarding employee interests and preferences (Vinichenko et al., 2019; Vrontis et al., 2022). Apart from data analysis, AI in HR impacts organizational structure. AI can help organizations build frameworks that are more adaptable and versatile. AI, for instance, can help identify changes in consumer preferences and sector trends, enabling HR managers to adjust job descriptions and organizational frameworks accordingly (Thite, 2018). Moreover, by identifying biases in job postings and recruitment processes, AI can help organizations establish more diverse and inclusive frameworks (Durana et al., 2022). The research proposes a conceptual framework to assess the influence of AI application domains in HR on promoting agility within HR, as illustrated in Figure 1.

3. Methodology

The methodological design of this study is based on the conceptual framework that was created in the previous section, determining the theoretical connection between AI applications and HR agility. The quantitative research method was used, which is in line with previous research studies that used SEM to establish causal relationships among latent variables. This conceptual-empirical connection allows making sure that the research design is properly aligned with the conceptual foundations of AI adoption and HR digitalization.

3-1. Research Design

The research design enables the gathering of data from a sizable population at a particular moment in time, the study approach is suitable for examining the effects of AI on the digitisation of human resources in Industry 4.0 (Hair et al., 2021) to determine the potential of HR, how HR digitisation creates the difference between myths and reality that elevates employee productivity about the success criteria (Murugesan, 2024). Industry 4.0 revolutionized human resources by using AI and IoT to automate payroll, performance reviews, and employment. Through improved decision-making, process simplification, and instant feedback, AI improved responsiveness and productivity. Additionally, it helped monitor workers' comfort, safety, and health while offering data-driven insights to boost engagement and lower burnout. However, challenges that surfaced included the potential for employment displacement, algorithmic prejudice, and data privacy concerns. Ethical considerations and technical improvements have to be balanced by HR. Achieving success requires transparency, equity, and alignment with corporate objectives. With these changes, the HR function experienced a substantial evolution. Descriptive and cross-sectional research approaches were perfect for examining how AI is affecting Industry 4.0's HR. By using a cross-sectional strategy, data might be gathered at a certain point in time, providing a summary of impacting HR practices without waiting for long-term data. The swift incorporation of AI into HR functions, like recruitment and staff efficiency, rendered this especially important. The descriptive method, conversely, concentrated on outlining the features of AI applications in HR, thereby facilitating the ID of patterns and comprehension of how AI was improving HR efficiency and adaptability. Through the integration of these methods, researchers managed to evaluate the outcome of AI on HR practices in real-time, identify biases, while offering valuable recommendations for enhancing HR digitization in Industry 4.0, and tackling concerns related to transparency and privacy.

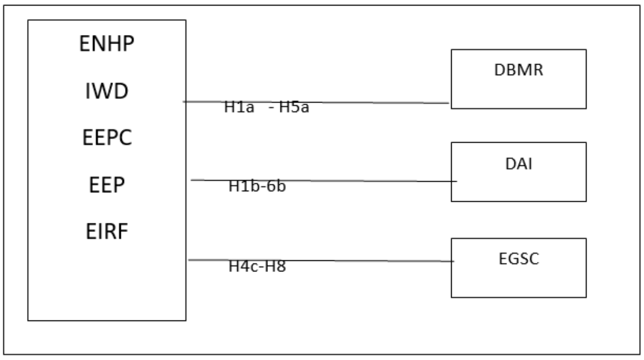

Fig. 1. Proposed Conceptual Model

3-2. Sampling and Population

The study's population included human resource professionals employed in the manufacturing, ITES, and service industries in Vijayawada. The chosen region was selected because of its varied range of sectors. The service sector was expanded to include private-sector banks. The study employed a multi-stage sampling technique, starting with the choice of a geographic region, followed by an assessment of businesses across each sector, and concluding with the selection of respondents from the chosen companies. After additional review, 282 of the 340 surveys sent out through a Google Form were deemed suitable for research, resulting in a 72% response rate. Based on previous research, a sample size of 282 can be considered acceptable. A minimum sample size of 200 is advised for SEM analysis, as stated by Kline (2023). Furthermore, Hair et al. (2021) indicate that, for structural equation modelling, a sample size of 200–400 is considered sufficient. Additionally, Tabachnick (2013) state that larger sample sizes are usually preferable and that SEM study necessitates a trial size of 100 at a minimum. A multi-phase sample strategy was used to choose certain businesses from the ITES, manufacturing, and service industries. Vijayawada was selected as the geographic emphasis for the first stage because of its industrial variety. Companies in each industry were graded in the second stage; the precise standards for this assessment were not stated, but it probably took into account elements such as the amount of activity, the size of the company, and the extent of technology adoption. HR specialists from the indicated companies were chosen to take part in the study in the last phase. A 72% response rate was achieved by distributing 340 questionnaires using Google Forms, of which 282 valid responses were received. A wide view of how AI is affecting HR procedures in many businesses was made possible by the diversity in this region. The city was ideally situated to investigate AI's role in HR digitization and agility, as it was home to a diverse array of firms, including private sector banks. Vijayawada provided insightful information about how AI improved productivity and efficiency as a center for manufacturing and IT. Sector-specific AI applications in

HR were captured by the study, which received responses from 72% of the industries polled. The city's compatibility with Industry 4.0 technologies further reinforced its appropriateness for investigating AI's potential to enhance HR procedures.

3-3. Scale Development and Validation

Through adapting similar literature closely, the new scales were created in order to capture the components applied in the model study. Through testing the scales for various validity and reliability parameters (Hinkin, 1995), the efficiency of the scales to capture the constructs was then proved. Hair (1986) argues that reliability means consistency of measurement over time, while validity means how well a scale can measure the thing it is meant to measure. Confirmatory factor analysis (CFA) in this study established validity and reliability of measures. Scales indicated strong construct validity and reliability, according to the outcomes from CFA. In particular, the composite reliability (CR) of all measures at values higher than the prescribed cutoff value of 0.7 indicates very high internal consistency. Additionally, the average variance extracted (AVE) of all constructs at values higher than the prescribed cutoff value of 0.5 attests to convergent validity that is strong. Therefore, employed scales in this study were determined to be applicable for measuring relevant constructs. The validity and reliability of the scales applied during an analysis of AI engagement in HR digitization in Industry 4.0 are gauged through Confirmatory Factor Analysis (CFA). Confirmatory Factor Analysis was applied to establish the measurement model and ascertain if the latent structures were accurately defined by the observed variables. Reliability and convergent validity of scales were ensured through the study's internal consistency, as indicated by Composite Reliability (CR) measures greater than 0.7 and Average Variance Extracted (AVE) measures greater than 0.5. Finally, by ensuring AVE values greater than Maximum Shared Variance (MSV) and Average Shared Variance (ASV), discriminant validity was ensured. Good model fit was reflected in the fit statistics of the model, which included: RMSEA = 0.042, CFI = 0.879, and GFI = 0.883. Data analysis was conducted using AMOS software for Structural Equation Modelling (SEM), a method by which complicated correlations among variables were tested, as well as SPSS for preliminary analysis. With Cronbach Alpha more than 0.8 for the majority of the constructs, the findings of CFA supported the validity and reliability of the scales employed in the study to ensure the proper measurement of HR agility and AI adoption in HRM.

3-4. Data Collection

A standardized survey was employed to gather data for the research. The initial component of the three-part tool includes demographic inquiries. The second segment focuses on AI uses in HRM, while the third and last part includes assessments of human resource agility. Both sections employed the five-point Likert scale.

3-5. Data Analysis

The preliminary statistics were analyzed by SPSS and Structural Equation Modelling (SEM) by AMOS 20. SEM was chosen as it enables the analysis of several interdependent relationships between latent variables at the same time, which is a strong test of the hypothesized theoretical model. The measurement model was confirmed by Confirmatory Factor Analysis (CFA) before hypothesis testing, and this was done to ensure that every latent construct was well represented by the observed indicators. SPSS was employed for the initial statistical examination of the whole data, whereas AMOS was utilized to assess the SEM. Multiple validity and reliability assessments were carried out on the scales utilized in this research, and the findings indicated that they were sufficiently robust to proceed with the study. SPSS and AMOS were employed for data analysis in the research because they can manage intricate datasets and conduct structural equation modeling (SEM). Basic statistics and data cleaning were performed by SPSS, while AMOS was utilized to evaluate the model's fit and investigate correlations between variables. The combination of these technologies guaranteed accurate and valid findings when analyzing how AI affects HRM.

3-6. Assessing the Assumptions of SEM

Through the analysis of skewness and kurtosis for each variable, the researcher validated multivariate normality, with all values residing between -2 and +2. They additionally employed maximum likelihood estimation, which relies on the premise of multivariate normality. They have managed missing data through listwise deletion, which eliminates instances with missing values from the analysis. The ultimate sample size of 282 exceeded the minimum sample size suggested for SEM analysis (Kline, 2023). Through the application of a priori model grounded in earlier studies and theoretical insights, they confirmed that the model's definition was accurate. Additionally, they utilized confirmatory factor analysis to evaluate the model's goodness of fit.

The standards aimed at the determination of reliability, discriminant validity, and convergent measures are indicated in Table 1. The construct dependability of the study is gauged by Table 1, also referred to as Cronbach's Alpha (Hundleby, 1968). Cronbach's alpha is expected to be greater than 0.70. The consistency of the constructs used in the study is assured by Table 1, indicating that the constructs have a Cronbach alpha measure > 0.8. A second measure of reliability, referred to as composite reliability, or CR, is reported in Table 1. The major application of the composite dependability is in route modelling, which also takes into consideration computation error (Fornell & Larcker, 1981). A Cronbach Alpha score of over 0.7 is equivalent to the CR threshold level. Average Variance Extracted (AVE) is a very important criterion for validity. The findings of the reliability and validity analysis of all constructs employed in the study are given in Table 1. Cronbach Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) values indicate that the measurement items are reliable in measuring the underlying theoretical constructs. Compared to other research constructs, the value of AVE quantifies the variance extracted by the items under the components. The estimated minimum of AVE's value is 0.5. All the constructs in the study satisfy these convergent validity criteria (Fornell & Larcker, 1981). For all of the latent variables used in the study, the maximum shared value (MSV) and average shared value (ASV) have to be less than the AVE in order to assess discriminant validity. The discriminant validity of the constructs to be analyzed is established in Table 1, which indicates that AVE is higher than the MSV and ASV figures for the constructs to be studied (Bagozzi & Yi, 1988). The observed Kaiser-Meyer-Olkin (KMO) statistics value of 0.872 in the study is greater than the minimum recommended value of 0.6, indicating that the sample is adequate and factor analysis is appropriate for the data.

Table 1. Reliability and Validity of the Constructs

Construct	α	CR	AVE	MSV	ASV	ENHP	IWD	EEPC	EEP	EIRF	DBMR	DAI	EGSC
Embedding new hires and payroll processing	0.925	0.917	0.552	0.514	0.456	0.876							
Improvement in workplace decisions	0.927	0.961	0.627	0.421	0.526	0.714	0.796						
Enhancing employee performance and comfort	0.826	0.911	0.599	0.510	0.412	0.769	0.675	0.875					
Elevating employee productivity	0.976	0.965	0.764	0.641	0.324	0.697	0.426	0.564	0.864				
Employee involvement and real-time feedback	0.923	0.817	0.521	0.347	0.214	0.867	0.567	0.463	0.513	0.764			
Differentiate between myth and reality	0.971	0.967	0.569	0.537	0.447	0.763	0.436	0.469	0.497	0.567	0.796		
Determine the potential of AI	0.843	0.899	0.574	0.423	0.471	0.741	0.469	0.567	0.326	0.476	0.476	0.736	
Evaluate and grade the success criteria	0.972	0.987	0.512	0.469	0.456	0.634	0.512	0.579	0.547	0.436	0.563	0.579	0.713

Table 1 indicates that all constructs have Cronbach's Alpha and CR values of over 0.70 and AVE values of over 0.50, confirming a high level of internal consistency and convergent validity of the scales used. Bartlett's test for sphericity is employed to assess if the correlation matrix is sufficient. The test shows a high significance at a level of $p< 0.001$, featuring a test value of 764.98 and a degree of significance less than 0.0001, suggesting that the correlation matrix reveals strong correlations among at least a few of the variables. Because the variables are not orthogonal, the assumption that the correlation matrix is an identity matrix is dismissed. Considering the substantial value of less than 0.05, it would be advantageous to conduct a factor analysis on the dataset. The demographic traits of the respondents, such as gender, age, education, and industry type, are summarized in Table 2 to provide a context for the study sample.

Table 2. Demographical Profile of the Respondents

Demographical variable	Category	No. of respondents	Percentage of the respondents
Gender	Male	158	56.02
	Female	124	43.97
Age	21-30	63	22.34
	31-40	132	46.80
	41-50	59	20.92
	>50	28	9.92
Education	Master's degree	127	45.03
	Bachelor's degree	155	54.96
Industry type	Manufacturing	68	24.11
	ITES	172	60.92
	Service sector	42	14.89

The statistics show that the respondents were mostly men, aged between 31 and 40 years, which is a balanced sample across manufacturing, ITES, and service industries, validating the representativeness of the sample.

4. Results, Analysis, and Interpretation

This segment contains the demographic profile of the respondent. Furthermore, this section presents the findings and their interpretations.

4-1. Profile of the Respondent

Table 2 indicates that 56.02% of the responses were from male participants, while 43.97% of the workforce was identified as female. Consequently, most of the responses gathered for this research came from males. Out of the participants, 22.34% fall within the age group of 21 to 30, while 46.80% are aged between 31 and 40. Consequently, individuals aged 31 to 40 contributed a significant share of the answers. Approximately, 54% of the respondents possess a bachelor's degree, while the rest have a master's degree in education. The large majority of respondents are pursuing a bachelor's degree. A total of 14% of the applicants are employed in the service sector, 24.11% work in manufacturing, and 60.92% are part of ITES companies.

The proposed conceptual model was evaluated through the Structural Equation Modelling (SEM) method, using Analysis of Moment Structures (AMOS 20) software (Anderson & Gerbing, 1988). It explores the relationship between HR Agility (i.e., dependent variable) and the facets of AI application (i.e., independent variables): Three causal connections between AI application and AI potential, AI application and the distinction between myth and reality, and AI application in evaluating success criteria. The beta and P values for the causal relationships of the previously mentioned variables can be found in Table 4. The dependent variable, the potential of AI, plays a crucial role across all five AI in HR dimensions, exhibiting beta values of -0.187, 0.526, 0.397, 0.178, and -0.296, respectively

Table 2 shows that 56.02% of the data came from male respondents, whereas 43.97% of the workforce was categorised as female. As a result, the majority of the responses obtained for this study were from men. Of the respondents, 22.34% are between the ages of 21 and 30, and 46.80% are between the ages of 31 and 40. As a result, respondents between the ages of 31 and 40 provided a sizable portion of the responses. A bachelor's degree is held by about 54% of the respondents, while the remaining respondents have a master's degree in education. The vast majority of those surveyed are working towards a bachelor's degree. A total of 14% of the respondents work in the service industry, 24.11% are in the manufacturing sector, and 60.92% are employed by ITES organisations. Only three of the five AI-related HR dimensions, whose beta values are 0.289, 0.268, and 0.426, respectively, had a substantial impact on myth and reality difference. The automated payroll system is the only one of the five AI-related HR dimensions that does not significantly affect the endogenous variable of success criteria. The other dimensions, with beta values of -.184, -0.419, 0.576, -.321, and 0.641, all demonstrate a substantial impact on success criteria.

Table 3. Fit Indices of the Conceptual Model

	CMNF/DF	RMSEA	CFI	IFI	GFI	AGFI	RMR	P
Model	1.653	0.042	0.879	0.897	0.883	0.768	0.006	0.1624
Recommend Standard	<2.89	<0.07	>0.90	>0.89	>0.89	>0.89	<0.07	>0.05

Table 3 displays the values of various goodness-of-fit indices. The previously mentioned fit indices yield these values: RMSEA = 0.042, RMR = 0.006, AGFI = 0.768, IFI = 0.897, GFI = 0.883, CFI = 0.879, and normed chi-square = 1.653 with a P value of 0.1624. All metrics, aside from AGFI, indicate the results of the proposed SEM within the acceptable thresholds.

Table 4 shows the standardized beta and significance (p) values of the causal relationships that were tested in the structural model. These findings evaluate the proposed relationships between dimensions of AI application and HR agility.

Table 4. Results of the Conceptual Model

Hypothesis	Path	Standardized coefficient	p-value	R2
H1a	Embedding new hires and payroll processing. Differentiate between myth and reality.	.289	***	0.628
H2a	Improvement in workplace decisions. Differentiate between myth and reality.	.108	.089	
H3a	Enhancing employee performance and comfort. Differentiate between myth and reality.	.268	***	
H4a	Elevating employee productivity. Differentiate between myth and reality.	.426	***	
H5a	Employee involvement and real-time feedback. Differentiate between myth and reality.	-.874	.251	
H2b	Embedding new hires and payroll processing. Determine the potential of AI.	-.187	***	.771
H6b	Improvement in workplace decisions. Determine the potential of AI.	.562	***	
H5b	Enhancing employee performance and comfort. Determine the potential of AI.	.397	***	
H1b	Elevating employee productivity. Determine the potential of AI.	.178	***	
H4b	Employee involvement and real-time feedback. Determine the potential of AI	-.276	***	
H7	Embedding new hires and payroll processing. Evaluate and grade the success criteria.	-.184	.052	0.446
H5c	Improvement at workplace decisions. Evaluate and grade the success criteria.	-.419	***	
H6c	Enhancing employee performance and comfort. Evaluate and grade the success criteria.	.576	.003	
H4c	Elevating employee productivity. Evaluate and grade the success criteria.	-.321	***	
H8	Employee involvement and real-time feedback. Evaluate and grade the success criteria.	.641	***	

The results of the SEM confirm that the use of AI has a considerable impact on HR agility in a variety of pathways, and the beta values are high in the most important dimensions. The results confirm the conceptual model and support the theoretical argument that the adoption of AI improves HR process agility. Every one of the three internal factors, referred to as the dimensions of HR Agility, is linked to each of the five external variables of AI implementation in HR that are analyzed in this research. Table 4 indicates that the five facets of AI in HR contribute to 77% of the variation in AI's potential. Having a coefficient value of 0.562, enhancement in workplace decisions is considered one of the most impactful dimensions. The potential of AI is negatively influenced by employee participation and immediate feedback. In contrast, just three factors of AI applications can account for 62% of the variation in the differences between myths and reality. The integration of new employees and payroll processing ranks highest, with a coefficient value of 0.289. The four HR AI aspects account for 44% of the variability in success criteria, with employee engagement and immediate feedback positively contributing, reflected in a high coefficient of 0.641. Enhancing employee productivity unexpectedly affects organisational design negatively, resulting in a coefficient value of -0.321.

Table 5. Comparison of Findings with Previous Studies

Theme/Variable	Findings of the Present Study	Findings of Previous Studies	Similarit/ Difference	References
AI in Recruitment	AI significantly improves recruitment efficiency through automation and data-driven selection.	Previous studies also reported enhanced recruitment accuracy using AI-based systems.	Similar	(Murugesan et al., 2023); (Nawaz, 2019)
AI in Performance Management	AI positively impacts performance tracking and feedback mechanisms.	Previous studies also found AI essential for continuous performance monitoring.	Similar	(Rydén & El Sawy, 2022; Vrontis et al., 2022)
Automated Payroll	The effect of AI on payroll automation was weaker and statistically insignificant.	Previous studies found automation in payroll to have a stronger impact in large-scale energy sector firms.	Different	(Sharma et al., 2022)
AI and Employee Well-being	AI improves employee safety and health monitoring through sensors and data analytics.	Previous studies observed similar results on AI enhancing workplace well-being.	Similar	(Saraswathi et al., 2023; Ugwu & Abdelrahman, 2020)
AI and HR Agility	AI adoption directly contributes to HR agility, enabling responsiveness and innovation.	Previous studies emphasized AI’s strategic importance for HR adaptability.	Similar	(Dima et al., 2024; Yawson et al., 2019)

Table 5 gives a comparative overview of the findings of the study and the existing literature. The findings are consistent with the majority of the previous research, confirming the positive impact of AI on HR digitalization and agility. Minor deviations, including the less powerful impact of automated payroll, reflect the contextual differences that are particular to the Indian organizational setting.

5. Discussion

The results of the current study align with the previous studies conducted by Murugesan et al. (2023) and Dima et al. (2024), which also emphasized the transformative nature of AI in improving HR digitalization and agility. Nevertheless, as compared to prior research, which was primarily concerned with recruitment and automation, the study expands the debate by combining AI applications with HR agility results, offering a more holistic view of the strategic potential of AI in Industry 4.0 settings. Since a competent expert offers them several benefits that increase productivity and revenue, managers are often concerned about the health and well-being of their employees. HR departments may screen and monitor employee well-being using related devices. Smartphones and tablets can gather numerous types of data, such as walking distance, food intake, and representative readings. With the information gathered, human resources personnel may identify difficulties that are affecting health and leading to medical problems and take appropriate precautions to avoid them. AI is being used quickly, despite worries about bias, data privacy, and ethics (Gartner, 2024). The benchmarking session in January 2024 revealed that 34% of HR leaders were investigating potential possibilities and use cases related to generative AI, a subset of wider AI. HR may use AI to accomplish its goal of enhancing worker well-being. To safeguard their representatives, they can scan gas pipes, hardware, and devices. For instance, since the critical factor is higher in gas pipelines, AI sensors can screen for it to prevent spills. The study found that improving employee health and safety has a significant impact on increasing HR agility through organisational design and ONA (Saraswathi et al., 2023). HR staff can discover elements, such as specific work hours or foundation disturbances, that distract a worker by employing a device that uses sensors to monitor employees and identify their movements. HR professionals might use it to compile information on eye strain while on duty (Mohanty & Mishra, 2020). Assume that a worker's productivity declines if they feel like dozing off for a few hours in the early evening. By setting up a life skills training program, HR can help its staff strike a balance between working and leading healthy lives. This will promise that workers actively concentrate on their tasks while on duty and guarantee increased output. This is the outcome of increasing agility through the digitisation of the HR process. Here, the findings corroborate the earlier research by Barman and Das (2018), Randhawa (2019), Yawson et al. (2019), and Gartner (2024). In AI-driven HRM systems, especially in Industry 4.0, establishing a balance between data protection and employee well-being needs significant thought. AI improved worker well-being by tracking health data, providing individualized training plans, and enhancing safety with environmental assistance and real-time feedback. However, because monitoring systems unintentionally exposed private data, the massive amount of data collected caused privacy issues. Companies secured employee approval, established clear regulations describing data usage, and guaranteed data security to achieve a balance. Even though AI increased output and enhanced employee satisfaction, it was essential to uphold robust privacy protections to make sure these tools were both practical and morally right for use in the workplace. To make new, realistic artefacts (at scale) that mimic the features of the training data without reproducing them, multiplicative AI may learn from prevailing artefacts. It may create a wide range of innovative material, including text, voice, video, music, graphics, software code, and product ideas (Dima et al., 2024). Astute companies are developing continuous self-service and AI literacy initiatives to raise awareness, expand knowledge, and establish a dynamic, iterative process for systematically gathering ideas and use cases to recognise the potential presented by GenAI.

Employees' direct views on official matters are rarely obtained. The HR department frequently struggles to comprehend the true feelings and emotions of its workers and develops several techniques, but none of them produce positive outcomes (Lepak, 2006). Applications of artificial intelligence can be used to solve this. While collecting feedback, AI devices can assist HR staff in comprehending the true feelings of their employees. After a meeting, cameras might take images of a representative to achieve ongoing criticism. According to Gartner (2024), interest in GenAI is still high. Across several business divisions, GenAI is being used by almost two-thirds of organisations. According to 40% of those surveyed since September 2023, their company has implemented GenAI across more than three business divisions. The images can be provided to staff in an abstract format, enabling machine vision to identify the representative's feelings and notify HR managers if an employee isn't genuinely happy. With appropriate input, an organization can be structured to adjust to a changing environment (SAP, 2016). This became possible through AI, which ensures agility in HR functions. The findings are consistent with earlier research suggested by Chowdhury (2019) and Yawson et al. (2019).

AI can detect patterns that signify depression and other mental health issues in employees. During the day, automated cameras can capture images of workers at set intervals. Computer vision can gather information on individual behavior norms from these images and analyze them, while those of unhappy individuals assess whether a worker is experiencing discomfort or despair. If computer vision identifies that an employee is feeling down, it can alert AI systems that may inform human resources.

HR staff can arrange counseling sessions to assist the employee in feeling more comfortable at work. In contrast to the studies by Pooja (2021), Gupta (2020) and Yawson et al. (2021), this may have a detrimental effect on the organisational design, as shown by the findings of previous research. All roles can use AI sensors to track truancy, but they cannot be used to monitor precise work hours. Sensors can be used for professions like administrative centre roles, which, for example, need employees to sit in their work areas to be profitable. However, that is not necessary for field jobs; therefore, AI sensors cannot be used to track labour hours for such jobs.

6. Implications

The research is useful to HR practitioners and policymakers in implementing AI-based approaches to increase HR agility. The suggested framework can help managers prioritize AI applications like automating recruitment, monitoring performance, and training employees to become more agile and efficient. These findings highlight the importance of ongoing upskilling and digital literacy training to equip HR professionals with AI integration.

This study adds to the existing literature on AI in HRM because it empirically confirms the connection between AI applications and HR agility. It builds on the theory of Industry 4.0 by introducing AI-enabled HR functions as the sources of organizational responsiveness and flexibility.

7. Conclusion

Although AI is still young, there are positive signs as its influence on human resource management (HRM). The 2024 Deloitte Generative AI Study found that 70% of highly GenAI competent companies said they were enhancing their existing services and products, and 45% said they would use the savings of GenAI projects to invest in additional innovation. The introduction of AI into the modern work environment allows to save more time through automation, personalisation, and actionable data insights. GenAI can speed up many HRM processes, including recruitment and performance management, and enable professionals to concentrate on more strategic and value-adding activities.

Other AI-based solutions can also improve the employee experience by providing career-advancing training suggestions, chatbot-based query solutions, and performance discussions based on data. The research contributes to the current theoretical understanding of the role of AI in HR agility and gives contextual support to the adoption of AI in emerging markets like India. Nevertheless, the use of AI also brings along new issues of data privacy, ethics, and network security. Before scaling AI-driven HR systems, organisations should protect employee data by having strong data governance systems.

7-1. Limitations

Since artificial intelligence is a relatively new and underutilised technology in India, few organisations are currently using it in HRM. As a result, the level of empirical analysis is limited. The application of AI in HR is still in its infancy, which restricts the comparative data, despite the fact that AI has been widely discussed in theory.

Moreover, the research was based on survey-based answers. Although empirical data were obtained with various organisations, further studies can use organisation-specific case studies or longitudinal analysis to gain a better understanding. The other weakness is the possibility of bias in AI algorithms. Systems trained with biased or incomplete information can perpetuate biases in HR decisions. The risk of job loss to automation is also a factor that is still in place, with AI taking over administrative HR functions.

7-2. Future Study

Further studies may be done by interviewing or conducting mixed-method analysis to understand the impact of AI on HR agility more holistically. The comparative studies might also include companies that have not implemented AI yet but intend to implement it to better capture the adoption intentions and readiness.

A quantitative methodology may be used to assess the quantifiable effects of AI-based HR decisions on employee turnover, engagement, and organisational performance. Furthermore, the investigation of employee attitudes and confidence in AI-based HR systems would be a valuable source of information, especially when it comes to the issue of transparency and equity.

AI has already proved to be efficient in recruitment, payroll, compliance, and performance management and it has also increased the strategic role of HR by predictive analytics and Organisational Network Analysis (ONA). In general, AI enables HR departments to move beyond administrative to strategic players, which will make organisations more agile and resilient in the Industry 4.0 era.

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