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A study of Artificial Intelligence impacts on Human Resource Digitalization in Industry 4.0

Umasankar Murugesan [a], Padmavathy Subramanian [b], Shefali Srivastava [a], Ashish Dwivedi [c,*]

[a] CHRIST (Deemed to be University), Bengaluru, India
[b] Kongu Engineering College, Erode, India
[c] Jindal Global Business School, OP Jindal Global University, Sonipat, India

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ABSTRACT

Artificial Intelligence (AI) has opened up tremendous opportunities in the workplace through robotics innovation, which envelops both AI and the Internet of Things (IoT). Precision, Efficiency, and Flexibility are considered the potential benefits of Industry 4.0. The implementation of Industry 4.0 requires a lot of changes, including the Human Resource (HR) function. In Industry 4.0, the HR capability is more critical and gives an upper hand to the organization. The HR capability should be more cautious and adaptable to adjust to the difficulties and requirements. We study the contributions of AI in HR digitalization and practices in Industry 4.0. 271 HR experts working in Information Technology (IT), Manufacturing, and administration are selected to participate in this review focusing on five AI applications in HR capability and three elements of HR readiness. The information collected was examined utilizing the Statistical Package for Social Sciences (SPSS) tool and Analysis of Moment Structures (AMOS). The results uncovered that hierarchical organization examination is a fundamental part of acquiring sustainable development. Adaptability and human asset capability are upheld by each of the five components of AI application areas of HR. Well-being and Safety improvement were viewed as vital components under the AI application in HR.

1. Introduction

In the era of Industry 4.0, the Human Resource (HR) function plays a critical role in bridging the gap between technology and human resources. Although technology is taking over most of the tasks traditionally performed by human resources, there is still a growing need for flexible HR functions to address the challenges of managing people. To achieve this flexibility, technology can help bring agility to the HR process. Agility, which is the ability to move quickly and smoothly, is not a new concept and has been adopted by major companies such as Google, Apple, Facebook, Amazon, and Microsoft. In the context of HR, agility means the ability to adapt and develop individuals and processes in response to rapid and unpredictable changes, to support people, key strategies, and organizational adaptability [1,2]. As an HR or Learning and Development (LandD) professional, being agile means being able to drive employee engagement and retention in alignment with the company's overall objectives. HR Agility is particularly suitable for volatile HR functions where standardization of functions is difficult [3,4].

In order for organizations to become agile, their workforce must focus on customer satisfaction and deliver value to them. However, since the HR function is not typically designed to provide direct incentives to the customer, it is often criticized for being slow to respond, which leads to dissatisfaction among employees. Therefore, organizations must encourage and empower HR to be more attentive and responsive to changing technologies and business needs in order to remain competitive and attract top talent. In an agile organization, HR continues to provide recruitment, development, performance management, and other HR functions, but using agile methodologies. There are three aspects of HR agility: the ability to quickly and efficiently identify issues that need to be addressed, the ability to reduce the time it takes to develop and implement a response, and the integration of analysis and design thinking to anticipate, plan, and target programs with the highest likelihood of success [2,5].

The rapid advancement of technology, especially the implementation of AI in HR, has brought about significant changes in HR processes and practices. As organizations increasingly move towards digitalizing their HR operations, it is crucial to understand the effects of AI on different aspects of HR such as employee productivity, health and safety, payroll processing, employee comfort, and real-time feedback [6]. Moreover, comprehending how these HR functions affect

* Corresponding author.
E-mail addresses: umasankar.m@christuniversity.in (U. Murugesan), padmavathy.mba@kongu.edu (P. Subramanian), shefali.srivastava009@gmail.com (S. Srivastava), Ashish0852@gmail.com (A. Dwivedi).

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organizational network analysis and design can offer insights on how organizations can utilize AI to enhance their overall efficiency and effectiveness. The purpose of this research article is to examine the correlation between AI and HR digitization and the impact of HR digitization on organizational network analysis and design [7,8]. The research objectives include investigating the relationship between AI and HR digitization in terms of measuring employee productivity, improving health and safety, automating payroll processing, enhancing employee comfort, and providing real-time feedback, identifying the benefits and challenges of HR digitization in the context of organizational network analysis and design, and evaluating the impact of HR digitization on organizational network analysis and design in terms of real-time feedback, enhancing employee comfort, improving health and safety, measuring employee productivity, and automating payroll processing (Sarkar and Maiti, 2022; 9). Through achieving these objectives, this research article aims to provide insights into the influence of AI on HR digitization and the implications of HR digitization on organizational network analysis and design. Additionally, this study aims to offer recommendations for organizations on how to effectively leverage AI to improve their HR processes and practices, and ultimately enhance their overall organizational efficiency and effectiveness [10]. This study discusses the two significant aspects of HRM: (i) Application areas of AI and (ii) agile aspect of HRM. The components measuring both aspects were adopted from the concept papers and web articles as very little research has been done so far. The study caters to the following Research Question (RQs):

RQ1: What is the potential impact of AI on HRM in meeting the demands of Industry 4.0?

RQ2: What extent can AI bring sustainability to HRM functions in Industry 4.0?

To answer the above RQs, following Research Objectives (ROs) have been framed.

RO1: To explore the current trends of AI in the Human Resource Management Practices (HRMP).

RO2: To assess the impact of AI on HRMP in order to cater the demands of industry 4.0.

RO3: To analyze the influence of AI on sustainability in industry 4.0.

Thus, to find the solutions of these framed objectives this study develops a conceptual framework by identifying the most prominent areas of application of AI. A comprehensive literature analysis is performed to analyze the studies relevant to application AI. Then, the proposed framework, contributes to the existing literature by prioritizing the implications. The results from the study could assist stakeholders to cater the challenges related to AI implementation.

2. Literature review

The human resources functions have evolved over the time and are considered to be dynamic [11]. The academic literature shows approaches using AI in the healthcare sector to achieve agility and the study showed the effectiveness of the HR function [3]. The key characteristic of AI is its ability to connect physical objects (or "things") to the Internet, such as vehicles, screens, pacemakers, electric motors, and more [9,12], as discussed by [13]. The practical implications of the Internet of Things (IoT) refer to the technical aspects of sensing, processing, and communication [8,14,15]. The estimation of different factors and the transmission of the deliberate information to AI are acknowledged as dependent on sensors set at the thing [16]. Sensors can gauge tremendously wide range of items and climate-related factors, like area, speed, temperature, condition of utilization, glitch, stress, and so forth [17,18]. The actual effect of detecting new data is profoundly itemized, continuous, naturally produced, dependable, and voluminous [12,17].

2.1. Role of AI on HR practices

In recent years, there has been a significant increase in the use of AI in various fields, including HRM. The advent of Industry 4.0 has led to an increased demand for automation, digitization, and agility in HR practices. AI has the potential to revolutionize HR practices, as it can enhance efficiency, accuracy, and decision-making in HR functions. One of the key areas where AI can make a significant impact in HR is recruitment and talent acquisition [19]. AI-powered algorithms can scan resumes and job applications to identify suitable candidates based on predefined criteria, reducing the time and effort required for manual screening. AI can also analyze candidate data to predict which candidates are most likely to succeed in a role, thereby improving the quality of the recruitment process.

Another area where AI can play a critical role is in employee engagement and retention. By analyzing employee data, AI algorithms can identify patterns and trends that may indicate low engagement or high turnover rates. This information can help HR professionals to take proactive measures to address these issues, such as implementing training programs or improving workplace culture [20]. AI can also be used to enhance learning and development programs for employees. By analyzing employee data, AI algorithms can identify knowledge gaps and recommend training programs to fill these gaps [21]. AI-powered learning platforms can personalize learning experiences to suit individual employee needs, thereby improving learning outcomes [22].

AI can also have a significant impact on performance management [23]. AI algorithms can analyze employee performance data to identify areas where improvements can be made. This information can be used to develop personalized performance improvement plans for individual employees, which can improve overall performance and productivity [24]. It plays a critical role in ensuring workplace safety and compliance. By analyzing data from sensors and other devices, AI algorithms can identify potential safety hazards and recommend preventive measures to mitigate risks. This can help to reduce workplace accidents and injuries, as well as ensure compliance with safety regulations [8,25].

Thus, to conclude it can be inferred that the use of AI in HR practices has the potential to revolutionize the way HR functions are carried out. AI can enhance efficiency, accuracy, and decision-making in recruitment, talent management, learning and development, performance management, and workplace safety [26]. However, it is essential to address concerns around bias and job displacement to ensure that the benefits of AI are realized without compromising ethical and social considerations [27]. Ultimately, the success of AI in HR practices will depend on how effectively organizations can balance the benefits of automation with the need for human empathy and judgment in HR practices [4,28].

2.2. Conceptual framework

2.2.1. Health and safety improvement in the workplace

The use of AI in HR can help in the identification and prevention of workplace hazards. AI-powered systems can analyze data from various sources such as sensors, cameras, and other devices to identify potential hazards in the workplace. This data can be used to create a safer working environment for employees [29]. AI can also help in the detection of health risks. For example, AI-powered systems can monitor employees' health data and identify any patterns that may indicate health issues. This information can be used to prevent potential health problems and provide employees with personalized health recommendations [30]. Another application of AI in HR is the use of chatbots to provide employees with instant assistance. Chatbots can be programmed to provide information on workplace health and safety guidelines, answer employees' questions, and even guide them through emergency situations [31]. AI can also be used to improve workplace ergonomics [32]. For instance, AI-powered systems can monitor employees' movements and identify any potential musculoskeletal disorders. This information can be used to make ergonomic adjustments to workstations, reducing the risk of workplace injuries [33].

2.2.2. Enhancing employee comfort

AI can help improve employee comfort in several ways. Firstly, AI-powered systems can analyze data from various sources, such as temperature sensors, to optimize the workplace environment for employee comfort. For instance, the system can adjust the temperature and humidity levels based on the number of employees present in the office [34]. Secondly, AI can help personalize the employee experience by providing personalized recommendations for employee comfort. For example, AI-powered systems can recommend desk or chair adjustments based on the employee's body type and preferences [35]. Thirdly, AI can help in the identification of workplace stressors and provide recommendations to alleviate them. AI-powered systems can monitor employee engagement levels, communication patterns, and other metrics to identify potential sources of stress in the workplace. This information can be used to implement strategies to improve employee comfort and reduce stress levels [36].

2.2.3. Employee productivity measurement

AI can help automate time-consuming administrative tasks, freeing up HR personnel to focus on other aspects of their job. This can lead to increased productivity for HR personnel, allowing them to spend more time on tasks that require their expertise [37]. AI can help measure employee productivity in real-time. AI-powered systems can analyze employee data, such as time spent on tasks and the completion rate of assignments, to provide real-time feedback on employee productivity. This information can be used to improve employee performance and identify areas for improvement [38]. AI can help measure employee productivity in a more objective manner. Traditional methods of measuring employee productivity, such as subjective evaluations, can be biased and unreliable [39]. AI-powered systems can provide more objective measurements of employee productivity, using data and analytics to make informed decisions [40].

2.2.4. Automating payroll processing

AI-powered systems can automatically calculate employee salaries and taxes, as well as process employee time-off requests and update employee information [41]. This can save HR professionals significant time and reduce the risk of errors in the payroll process. Furthermore, AI can help improve the accuracy of payroll processing. With its ability to analyze data and identify patterns, AI can help identify potential errors in payroll processing, such as duplicate payments or incorrect tax calculations. This can help reduce the risk of payroll-related errors and improve overall accuracy [42]. Finally, AI can help ensure compliance with payroll regulations. AI-powered systems can monitor payroll processing for compliance with legal requirements, such as minimum wage laws and overtime regulations. This can help reduce the risk of non-compliance and potential legal issues for the organization [43].

2.2.5. Real-time feedback

AI-powered systems can help provide real-time feedback to employees in several ways. Firstly, AI can help track employee performance in real-time, providing feedback on progress and identifying areas for improvement [44]. This feedback can be customized based on the individual needs of each employee, helping to improve their performance in specific areas. Secondly, AI can help provide feedback in a more objective manner. Traditional methods of providing feedback, such as subjective evaluations, can be biased and unreliable. AI-powered systems can provide more objective feedback based on data and analytics, helping to improve the accuracy of the feedback provided [45]. Finally, AI can help provide feedback in a more timely manner. With its ability to process large amounts of data quickly, AI-powered systems can provide feedback in real-time or near real-time, allowing employees to take action to improve their performance immediately [46].

2.2.6. Impact on digitization of HR

AI-powered systems can help automate many HR functions, including recruitment, onboarding, performance management, and employee engagement. For instance, AI can help automate the screening and shortlisting of job applications, reducing the time and effort required for manual processing [47,48]. AI can also help automate the onboarding process by providing personalized training and development programs to new hires [49]. Furthermore, AI can help track employee performance in real-time, providing data-driven insights that can be used to improve performance management and employee engagement [50]. The impact of AI in HR on digitization extends beyond operational efficiency [51]. AI can also help improve the quality of HR decisions by providing data-driven insights that can be used to inform strategic decision-making [52]. For example, AI-powered systems can help identify skills gaps in the workforce, enabling HR professionals to develop targeted training and development programs to upskill employees [53].

2.2.7. Organizational network analysis

AI-powered systems can help automate the collection and analysis of data for Organizational Network Analysis (ONA). For instance, AI can analyze email communication patterns to identify the key influencers and opinion leaders in an organization [54]. AI can also analyze social media data to identify the informal networks that exist within an organization [55]. Furthermore, AI can analyze data from employee surveys to identify the factors that influence employee engagement and collaboration [56,57]. The impact of AI in HR on ONA extends beyond data collection and analysis. AI can also help identify and address network gaps and inefficiencies. For example, AI-powered systems can identify communication breakdowns and bottlenecks, enabling HR professionals to develop targeted interventions to improve communication and collaboration [58].

2.2.8. Organizational design

AI-powered systems can help automate the analysis of data related to organizational design. For example, AI can analyze data on job performance, skills, and experience to identify the most suitable candidates for a particular role. AI can also analyze data on employee preferences and interests to identify potential areas of talent development [45,59]. The impact of AI in HR on organizational design extends beyond data analysis. AI can also help organizations design more flexible and adaptable structures. For example, AI can help identify changes in customer demands and market trends and enable HR professionals to redesign job roles and structures to respond to these changes [60]. Furthermore, AI can help organizations design more inclusive and diverse structures by identifying potential biases in job descriptions and recruitment processes [46].

To assess the impact of AI application areas of HR on bringing agility in HR, the study proposes a conceptual framework as mentioned below: (See Fig. 1).

3. Methodology

3.1. Research design

The study utilized a descriptive research design that follows a cross-sectional approach. The research design is appropriate for investigating the impact of AI on human resource digitalization in Industry 4.0 as it allows for the collection of data from a large population at a specific point in time [61].

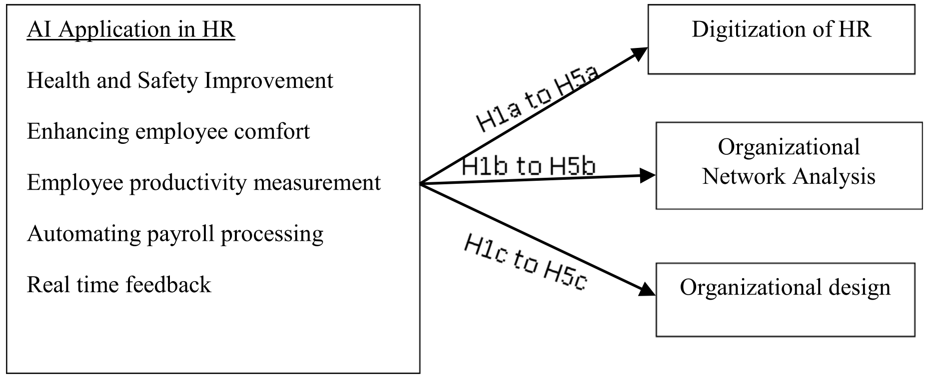

Fig. 1. Proposed conceptual model.

3.2. Population and sampling

The population of this study consisted of human resource professionals working in IT, ITES, Manufacturing, and service sectors in Chennai and Bengaluru. These two cities were selected as they encompass various industry types. Private sector banks were included under the service sector. A multi-stage sampling technique was used, with the first stage being the selection of geographical location, the second stage being the ranking of firms in each sector, and the third stage consisting of the selection of respondents from the selected firms. A total of 360 questionnaires were sent through a google form, and 271 questionnaires were eligible for analysis after further scrutinizing, with a response rate of 75%. A sample size of 271 can be justified based on previous research studies. According to [62], a sample size of at least 200 is recommended for SEM analysis. Additionally, [61] suggest that a sample size of 200 to 400 is considered adequate for structural equation modeling. Furthermore, [63] state that a sample size of at least 100 is required for SEM analysis, and larger sample sizes are always better.

3.3. Scale development and validation

To measure the constructs used in the research model, new scales were developed by modifying closely relevant literature. The scales were then tested for various validity and reliability measures to ensure their effectiveness in measuring the constructs [64]. According to [65], validity refers to the extent to which a scale measures what it is intended to measure, while reliability refers to the consistency of measurement over time. In this study, the validity and reliability of the scales were tested using confirmatory factor analysis (CFA). The results of the CFA indicated that the scales had good construct validity and reliability. Specifically, the composite reliability (CR) values of all constructs were greater than the recommended threshold value of 0.7, indicating high internal consistency. Additionally, the average variance extracted (AVE) values of all constructs were greater than the recommended threshold value of 0.5, indicating good convergent validity. Therefore, the scales used in this study were deemed suitable for measuring the constructs of interest.

3.4. Data collection

A structured questionnaire was used to collect the data to support the research. The instrument consists of three parts, with the first part consisting of demographic questions. The second part is related to AI applications in HRM, and the third and final part consists of statements measuring Human Resource Agility. Both parts two and three used the five-point Likert Scale.

3.5. Data analysis

The collected data were analyzed using SPSS for primary statistical analysis, and the proposed model was tested using AMOS. The scales used in this study were tested for various validity and reliability measures, and the result proved to be good to proceed with the investigation.

3.6. Assessing the assumptions of SEM

The researcher ensured multivariate normality by examining the skewness and kurtosis values of each variable, and all values fell within the acceptable range (−2 to +2). Additionally, they used maximum likelihood estimation, which assumes multivariate normality. They have addressed missing data by using the listwise deletion method, which removes cases with missing values from the analysis. The final sample size of 271 exceeded the recommended minimum sample size for SEM analysis [66]. They ensured correct model specification by using an a priori model, based on previous literature and theoretical background. They also conducted confirmatory factor analysis to assess the goodness-of-fit of the model.

Table 1 reveals the criteria for calculating Convergent, discriminant validity, and reliability measures. Table 1, denoted by $\boldsymbol{\alpha}$, is otherwise called Cronbach Alpha, which measures the reliability of the construct in the study [67]. The expected value of Cronbach alpha is anything above 0.70. From Table 1, it is identified that the constructs having the Cronbach alpha value > 0.8, which confirms the reliability of the variables used in the study. Table 1 encompasses another reliability measure, namely CR, which stands for Composite Reliability. This composite reliability is mainly used in path modeling, which accounts for error also in the calculation [68]. The threshold level for CR is the same as the Cronbach Alpha value of greater than 0.7. When it comes to validity, the essential criteria is Average Variance Extracted (AVE). The value of AVE explains the variance extracted by the items under the components while comparing with the other constructs in the study. The expected minimum value of the AVE is 0.5. All the constructs used in the study satisfy these criteria of convergent validity [68]. To assess the discriminant validity, both Maximum Shared Value (MSV) and Average Shared Value (ASV) should be less than the AVE for all the latent variables included in the study. From Table 1, it is found that AVE is higher than both the MSV and ASV values for the constructs included in the study, which confirms the existence of Discriminant Validity of the Constructs included in the study [69].

The Kaiser–Meyer–Olkin (KMO) statistics value observed for the study is 0.872, which is greater than the minimum recommended value of 0.6, indicating that the sample is adequate and factor analysis is appropriate for the data. The adequacy of the correlation matrix is tested using Bartlett's test of Sphericity. The test results show that the correlation matrix has significant correlations among at least some of the variables, as the test is highly significant at a level of $p < 0.001$, with

Table 1
Reliability and validity of the constructs.

Constructs	α	CR	AVE	MSV	ASV	HSI	EEC	EPM	APP	RTF	DHR	ONA	OD
Health and Safety Improvement	0.953	0.929	0.652	0.629	0.504	**0.807**							
Enhancing employee comfort	0.938	0.934	0.587	0.54	0.500	0.700	**0.766**						
Employee productivity measurement	0.928	0.933	0.581	0.51	0.462	0.731	0.681	**0.763**					
Automating payroll processing	0.978	0.966	0.778	0.537	0.332	0.607	0.571	0.532	**0.882**				
Real time feedback	0.901	0.895	0.523	0.509	0.380	0.684	0.592	0.533	0.555	**0.723**			
Digitization of HR	0.965	0.923	0.503	0.323	0.245	0.490	0.517	0.483	0.418	0.410	**0.709**		
Organizational Network Analysis	0.900	0.898	0.570	0.491	0.462	0.682	0.669	0.734	0.578	0.566	0.481	**0.754**	
Organizational design	0.945	0.915	0.730	0.645	0.544	0.790	0.766	0.716	0.618	0.672	0.548	0.737	**0.854**

Table 2
Demographic profile of respondents.

Demographic Variable	Category	No of Respondents	Percentage of the Respondents
Gender	Male	131	48.3
	Female	140	51.7
Age	21–30	89	32.8
	31–40	121	44.6
	41–50	42	15.5
	>50	29	10.7
Education	Master's degree	95	35.0
	Bachelor's degree	176	65.0
Industry Type	Manufacturing	80	29.5
	IT and ITES	129	47.5
	Service Sector	62	23.0

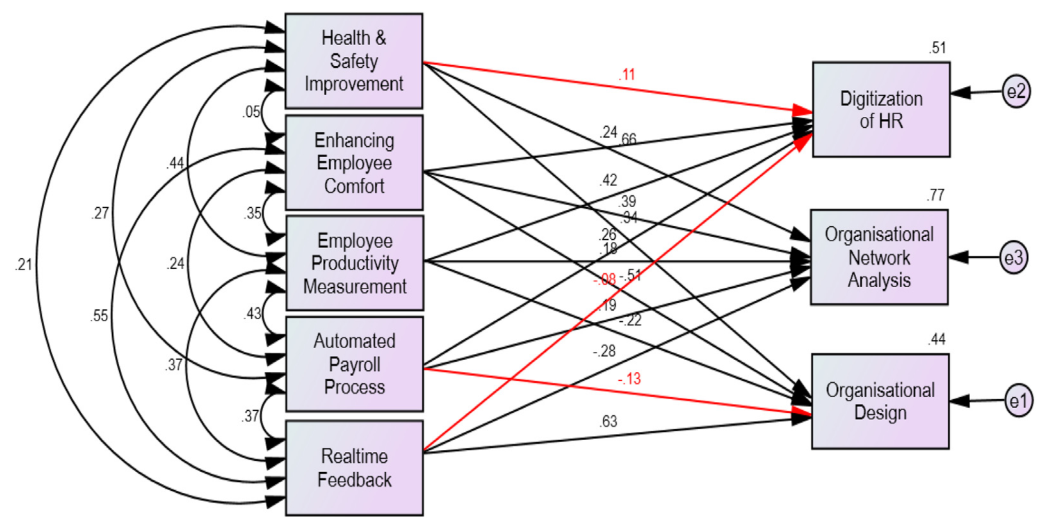

Fig. 2. Hypothesized Conceptual Model.

a test value of 874.98 and a degree of significance less than 0.0001. Therefore, the hypothesis that the correlation matrix is an identity matrix is rejected, meaning that the variables are not orthogonal. The significant value of less than 0.05 suggests that conducting a factor analysis on the dataset would be worthwhile.

4. Results, analysis and interpretation

In this section, the demographic profile of the respondent is discussed. Further, the results and interpretations are provided under this section.

4.1. Profile of the respondent

Table 2 depicts that 51.7% of the employees belong to the female category, whereas 48.3% of the data are received from the male respondents. Hence, females dominated the responses attained for this study. 44.6% of the respondent's age group are 31–40, and 32.8% are between 21 and 30. Hence a significant number of response was received from respondents of 31–40 years of age. Around 65% of the respondents hold a bachelor's degree, and the remaining respondents are have an education qualification of a master's degree. A majority of the respondents are pursuing a bachelor's degree. 47.5% of the respondents belong to IT and ITES organization, 29.5% of the respondents belong to the Manufacturing sector, and 23% of the respondents are employees of the service sector.

Structural Equation Modelling (SEM) technique was adopted to test the proposed conceptual model using Analysis of Moment Structures (AMOS 20) software [70]. It analyses the path relationship between the dimensions of AI application (i.e., Independent variables) and the dimensions of HR Agility (i.e., Dependent variable).

Fig. 2 portrays three causal relationships between AI Application to Digitization of HR, AI Application and Organisational Network Analysis, and AI Application and Organisational Design. The lines marked in red are statistically insignificant. From Table 4, the beta value and P-value belong to the above said variables' causal relationships are derived. All the five dimensions of AI in HR are showing highly significant value towards the dependent variable Organisational Network

Table 3
Fit indices of the conceptual model.

	CMIN/DF	RMSEA	CFI	IFI	GFI	AGFI	RMR	P
Model	1.563	0.043	0.997	0.997	0.993	0.868	0.006	0.154
Recommended Standard	<3.0	<0.08	>0.90	>0.90	>0.90	>0.90	<0.08	>0.05

Table 4
Results of the conceptual model.

Hypothesis	Path	Standardized Co-efficient	*P*-value	R^2
H1a	Employee Productivity Measurement → Digitization of HR	.422	***	0.508
H2a	Health and Safety Improvement → Digitization of HR	.109	.090	
H3a	Automated Payroll Process → Digitization of HR	.261	***	
H4a	Enhancing Employee Comfort → Digitization of HR	.238	***	
H5a	Real time Feedback → Digitization of HR	−.084	.247	
H4b	Real-time Feedback → Organisational Network Analysis	−.278	***	0.772
H5b	Enhancing Employee Comfort → Organisational Network Analysis	.386	***	
H6b	Health and Safety Improvement → Organisational Network Analysis	.660	***	
H1b	Employee Productivity Measurement → Organisational Network Analysis	.180	***	
H2b	Automated Payroll Process → Organisational Network Analysis	.194	***	
H6c	Enhancing Employee Comfort → Organisational Design	−.514	***	0.440
H5c	Health and Safety Improvement → Organisational Design	.339	***	
H4c	Employee Productivity Measurement → Organisational Design	−.222	.004	
H7	Automated Payroll Process → Organisational Design	−.129	.064	
H8	Real-time Feedback → Organisational Design	.630	***	

Analysis, and their beta values are −0.278, 0.386, 0.660 0.180, and 0.194 respectively. Out of five dimensions of AI in HR, only three dimensions have a significant influence on the Digitisation of HR, and their beta values are 0.422, 0.261, and 0.238 respectively. Out of five AI in HR dimension, one dimension named automated payroll system is not significant with the endogenous variable organizational design, the other dimensions are showing the significant influence on organizational design, and their beta values are −.514, 0.339, −0.222, and 0.630.

Table 3 displays the values of various goodness of fit indices. The values of the mentioned fit indices, normed chi-square is 1.563 P value = 0.154, RMR = 0.006, AGFI = 0.868, IFI = 0.997, GFI = 0.993, CFI = 0.997, RMSEA = 0.043. Except for AGFI, other values disclose the results regarding the fit of the proposed model within the threshold limits. The above values aptly fit the data in the proposed model.

Table 4 depicts the result of the three causal relationships between AI application areas and three dimensions of HR Agility as portrayed in the conceptual model as per Fig. 2. The five dimensions of AI application in HR, which are treated as exogenous variables in this study, are individually connected with each of the three endogenous variables, namely dimensions of HR Agility. Table 4 depicts that 77% of the variance in the Organisational Network Analysis is contributed by all the five dimensions of AI in HR. Out of that, Health and Safety Improvement are considered as a highly influencing dimension with a coefficient value of 0.660. The real-time feedback negatively contributes towards the variation in the organizational network analysis. On the other side, only three dimensions of AI applications are accounted for 51% of the variance in the Digitisation of HR. Employee productivity measurement tops the contribution with 0.422 as coefficient value. Four dimensions of AI in HR influence 44% of the variance in Organisational Design, and real-time feedback positively influence with a high coefficient value of 0.630. Surprisingly enhancing employee comfort negatively affects the organizational design with a negative coefficient value of −0.514.

5. Discussion

Employee health and well-being are a significant worry for managers as a solid specialist give different advantages to them, leading to expanded efficiency and income [71]. HR groups can use associated gadgets to screen and track worker well-being. Wearables can accumulate different information like food admission, strolling distance, and indispensable readings of representatives. Given the data accrued, HR staff can locate issues that are affecting well-being and causing medical problems and take suitable measures to keep away from them. HR needs to improve laborer well-being, and they can utilize AI to achieve that task. They can screen machines, hardware, and gas pipelines to protect their representatives [72]. For example, AI sensors can screen the crucial factor in gas pipelines to avoid any spillage because of the higher critical factor. The study identified that employee health and safety improvement is a highly influencing element in bringing agility in HR through ONA and organizational design.

A technology tracks the employees' eyes using sensors to identify its movement based on which HR personnel can distinguish factors like explicit work hours or foundation commotions that divert a worker. It can help HR people to assemble data on eye distraction while working on duty [73]. Suppose a worker feels snoozing during a couple of hours in the early evening, and their efficiency diminishes. HR can facilitate their employees to balance between their healthy living and working by arranging a life skill training program. This will ensure the employees actively concentrate on their work while they are on duty and promise higher productivity. This is the result of digitizing the HR process, which enhances agility. Here the results support the previous literature by [74–76].

It is sporadic to get honest feedback from employees in terms of official issues. Often, the HR department finds it hard to understand employees' real feelings and emotions and come out with a lot of strategies, but none of them are giving fruitful results [77]. This can be sorted out by incorporating AI applications. AI gadgets can help the HR personnel to understand the genuine emotions of their workforce while gathering criticism. Cameras can catch pictures of a representative after a gathering to accomplish constant criticism. The images can be sent absurd to the workers where computerized vision can identify feelings of the representative and send cautions to HRM's if a worker is not sincerely glad. Designing an effective organization to adopt a dynamic environment can be possible with the correct feedback [78]. AI made this possible ensures agility in the HR function. The result adhere to previous studies proposed by [3,76].

With the assistance of AI, AI can recognize designs characteristic of sadness and other psychological maladjustments in workers. Automated cameras can click pictures of workers at specific interval during the whole day. Computerized vision can remove personal conduct standards data from those pictures and contrast them, and those of discouraged individuals decide if a worker is experiencing uneasiness or desolation. Assuming computerized vision tracks down that a worker feels discouraged, it can impart signs to AI gadgets that can alarm HR.

HR staff can coordinate guiding meetings for that worker to improve his consolation at work. This may negatively impact the organizational design as identified by the results from existing study, and it is in contrast with the study by [79–81].

AI sensors to follow truancy can be executed for all positions, yet not to screen exact work hours. For example, administrative center positions expect workers to sit on their work areas for being profitable, and thus sensors can be executed for such jobs. Notwithstanding, field occupations do not need that, and AI sensors cannot be carried out to follow work hours for these sorts of professions. This is following the result proposed from the study by [74].

6. Conclusion, limitations and scope for future study

Carrying out AI in HRM gives numerous benefits to the HR department and employees. However, those advantages accompany a few network safety dangers and lawful concerns. Assembling more worker information implies expanded protection concerns, and more gadgets accompany more noteworthy prospects of network safety assaults. Before executing AI for HR the board, organizations need to ensure that their workers' information is not undermined. Associations likewise need to fabricate information-driven security to screen information itself and not simply organization to limit network protection dangers.

The study has addressed the application of AI concepts in various possible areas of HRM. These areas may not be there in the regular stream of activities. Still, it is trying to impose the importance of addressing the same—the dimensions measured under that showcase human aspects enhancement with the help of AI. The result revealed the way these aspects influence the agile capability of HRM. Digitization of HR and ONA is closed related technological implication in HR, enabling the iterative process of function. Both of the above aspects need an excellent organizational design to support the implementation and progress. Thus this study paved a new way by linking two elements prevailing today's Industry 4.0 era.

There are not many businesses using AI in their HRM or creating AI based HR software because it is still a very new and low-use field, particularly in India. As a result, it is challenging to compile a thorough study because the majority of businesses only use AI to a limited degree in the HR process. Even though AI as a subject has received extensive research, the ability to examine the true effectiveness and ramifications that AI involves is limited in the absence of a sufficient number of organizations who employ AI in their HR practices. The number of interviews may be larger to make this study more relevant. The responses of the interviewees, however, may be compared and contrasted.

As this study has demonstrated, the use of AI in recruitment is still a relatively new topic. More AI-related research should be conducted in the future to get a better picture of the subject. Although empirical findings from several organizations were used in this study, when more information about AI becomes available, an organization-specific study could be conducted. Organizations that do not currently use AI but intend to do so in the future could be included in the study to gain a broader perspective on the subject. Despite the potential benefits of AI in HR, there are also challenges and concerns that need to be addressed. One of the main concerns is the potential for bias in AI algorithms. If AI algorithms are trained on biased data, they may perpetuate and even amplify biases in the HR practices. Another concern is the potential for job displacement due to automation. As AI takes over more HR functions, there is a risk that some HR professionals may lose their jobs.

Furthermore, using a quantitative approach, it could be investigated how AI based HR decisions have impacted company success and turnover in numerical terms. Because there are trust issues with AI, employees' perspectives and experiences with AI-based HR practices could be studied to gain more perspectives on this topic.

List of Abbreviations

1. Artificial Intelligence (AI)
2. Human Resource (HR)
3. Internet of Things (IoT)
4. Statistical Package for Social Sciences (SPSS)
5. Structural Equation Modelling (SEM)
6. Analysis of Moment Structures (AMOS)
7. Information Technology (IT)
8. Human Resource Management Practices (HRMP).
9. Confirmatory factor analysis (CFA)
10. Composite reliability (CR)
11. Average variance extracted (AVE)
12. Maximum Shared Value (MSV)
13. Average Shared Value (ASV)
14. Kaiser-Meyer-Olkin (KMO)

Declaration of competing interest

The authors have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report.

Data availability

Data will be made available on request.

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