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PLS-SEM-Based Investigation of AI's Transformative Impact on Human Resources Practices: Insights from Industry 4.0 HR Digitalization

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Abstract
This study employs PLS-SEM to investigate the impact of artificial intelligence (AI) on human resource (HR) digitalization within the framework of Industry 4.0. Employing a descriptive research design coupled with analytical and empirical methods, data were collected from 271 HR professionals in Chennai and Bengaluru, India, representing diverse industries including IT, ITES, manufacturing, and services. The study utilized a structured questionnaire to gather demographic information and assess AI applications in HR, utilizing a five-point Likert Scale. Based on data analysis, the study found significant positive relationships between various factors, including quantifying employee productivity, workplace health and safety, performance feedback, payroll automation, and employee well-being, with HR digitalization, organizational network analysis (ONA) and organizational design. Additionally, AI was shown to enhance organizational design and agility within HR functions. These findings highlight the transformative capacity of AI in reshaping HR practices, organizational dynamics, and workforce well-being in thedigital age. By providing empirical evidence, this study contributes to existing literature and outlines implications for HR professionals, organizational leaders, policymakers, and researchers, emphasizing the need for continued investment in AI technologies and strategicHR initiatives to navigate the challenges and opportunities of Industry 4.0.

Keywords: AI, SEM, Digitization, Industry 4.0, Human resource management.

Introduction
The advent of Industry 4.0 marks a profound shift in the global industrial landscape, propelled by the integration of advanced technologies such as artificial intelligence (AI), the Internet of Things (IoT), and automation (Bujold et al., 2023). This paradigmatic shift promises to revolutionize traditional industrial practices, offering unprecedented levels of efficiency, productivity, and agility (Wang et al., 2023). At the heart of this transformative era lies the human resources (HR) function, tasked with navigating the complexities of workforce management amidst rapid technological advancements(Goswami et al., 2023). Despite the proliferation of AI and digitalization, the role of HR remains indispensable, serving as the linchpin for organizational success in the digital age (Budhwar et al., 2023).

In the dynamic landscape of Industry 4.0, characterized by rapid technological disruption and evolving consumer demands, the agility of HR becomes paramount(Tuomi, 2018). Agility in HR encompasses the ability to swiftly adapt to changing circumstances, optimize processes, and align workforce strategies with organizational objectives (Alnamrouti et al., 2022). This agility is exemplified by industry leaders such as Facebook, Google, Amazon, Apple, and Microsoft, where HR practices are tailored to foster employee engagement, retention, and innovation in the face of constant change (Budhwar et al., 2022).

However, amidst the technological advancements and the imperative for agility, HR faces unique challenges within the Industry 4.0 framework (Votto et al., 2021). The traditional functions of HR, including recruitment, talent management, and performance evaluation, are increasingly being influenced by AI and automation (Panda et al., 2023). While these technologies offer unprecedented opportunities for efficiency and precision, they also pose challenges in terms of workforce integration, ethical considerations, and job displacement (Singh & Shaurya, 2021).

Against this backdrop, this study aims to investigate the impact of AI on HR practices within the context of Industry 4.0. By examining the intersection of AI technology and HR management, this research seeks to elucidate the opportunities and challenges presented by AI adoption in enhancing HR readiness, adaptability, and effectiveness. Specifically, the study focuses on understanding how AI influences key HR functions such as recruitment, talent acquisition, learning and development, performance management, and workplace safety.

To achieve these objectives, the study employs a structured questionnaire survey involving 271 HR professionals from diverse industries, including Information Technologies, Manufacturing, and Administration sectors. By gathering insights from HR practitioners across different domains, the research aims to provide a comprehensive understanding of AI's impact on HR practices and its implications for organizational success in the Industry 4.0 era.

Overall, this study seeks to contribute to the existing body of knowledge by offering empirical insights into the transformative role of AI in HR management and providing practical recommendations for organizations to harness the potential of AI technology effectively.

2. Literature Review

2.1. Impact of AI on HR Operations

The integration of artificial intelligence (AI) into human resource (HR) operations has catalyzed transformative changes across various organizational functions(Orosoo et al., 2023). AI technologies, such as machine learning algorithms and natural language processing, have revolutionized recruitment processes by automating candidate screening and selection tasks(Malik et al., 2022). These AI-powered tools analyze vast datasets from resumes, job descriptions, and candidate profiles to identify the most qualified candidates efficiently, thereby saving HR professionals valuable time and resources (Jatobá et al., 2019). Additionally, AI-driven chatbots and virtual assistants have enhanced the candidate experience by providing immediate responses to inquiries and guiding candidates through the application process(Czarnowski & Pszczólkowski, 2020). Beyond recruitment, AI has also revolutionized employee engagement and retention strategies by analyzing sentiment data from various sources to identify factors contributing to low engagement and turnover risk (Shahzad et al., 2023). This enables HR professionals to proactively address issues such as dissatisfaction and burnout, ultimately improving overall employee retention rates.

Furthermore, AI technologies have been instrumental in optimizing learning and development initiatives within organizations. AI-powered learning platforms deliver personalized training content tailored to individual employee needs and learning preferences(Xin et al., 2022). By analyzing employee performance data and feedback, these platforms recommend relevant courses and resources to help employees upskill and reskill in alignment with organizational goals. In the realm of performance management, AI-driven analytics tools provide managers with actionable insights and recommendations for performance improvement by analyzing real-time data on key performance indicators (Rožman et al., 2023). Additionally, AI-powered feedback systems deliver timely and objective feedback to employees, fostering a culture of continuous improvement and development(Yang, 2022). Overall, the integration of AI into HR operations has led to increased efficiency, accuracy, and effectiveness in managing the workforce, positioning AI technologies as indispensable tools for HR professionals in the modern digital age.

2.2. Theoretical Framework

2.2.1. Enhancement of Workplace Health and Safety

The theoretical framework for enhancing workplace health and safety through the integration of artificial intelligence (AI) revolves around the utilization of AI-driven technologies to proactively identify and mitigate potential hazards in the workplace(Rožman et al., 2022). AI-powered systems, equipped with advanced data analytics and sensor technologies, analyze various sources of data, including environmental conditions, employee health records, and safety incident reports, to identify patterns and trends indicative of potential risks (Sony & Mekoth, 2022). By leveraging machine learning algorithms, these systems can predict and prevent workplace accidents by identifying safety hazards and recommending preventive measures in real-time (Neumann et al., 2021). Additionally, AI-driven chatbots and virtual assistants can provide employees with immediate access to safety information and guidance, enhancing awareness and adherence to safety protocols(Ammirato et al., 2023). Overall, the theoretical framework emphasizes the proactive use of AI technologies to create a safer and healthier work environment, thereby reducing the incidence of workplace injuries and promoting employee well-being.

2.2.2. Augmenting Employee Well-being

The theoretical framework for augmenting employee well-being through AI centers on leveraging AI-driven technologies to enhance various aspects of employee comfort, satisfaction, and mental health in the workplace(Madsen, 2019). AI-powered systems, equipped with sentiment analysis and emotion recognition capabilities, can analyze employee interactions, feedback, and behavioral patterns to identify indicators of stress, burnout, or dissatisfaction (Theotokas et al., 2024). By providing personalized recommendations and interventions, such as mindfulness exercises, relaxation techniques, or ergonomic adjustments, AI systems can help alleviate stress and improve overall employee well-being (Vereycken et al., 2021). Additionally, AI-driven chatbots and virtual assistants can serve as confidential channels for employees to seek support, guidance, or mental health resources, thereby reducing barriers to access and stigma associated with seeking help (Vereycken et al., 2021). Overall, the theoretical framework underscores the role of AI in fostering a supportive and conducive work environment that prioritizes employee well-being and mental health.

2.2.3. Quantifying Employee Productivity

The theoretical framework for quantifying employee productivity through AI focuses on leveraging AI-driven analytics and data-driven insights to measure, monitor, and optimize employee performance in the workplace(Adel, 2022). AI-powered systems, equipped with advanced algorithms and machine learning capabilities, can analyze vast amounts of employee data, including work output, task completion rates, and time allocation, to generate objective metrics of productivity (Vrchota et al., 2020). By providing real-time feedback and performance insights, AI systems enable managers to identify areas of improvement, allocate resources effectively, and optimize workflow processes to enhance overall productivity (Queiroz et al., 2022). Additionally, AI-driven tools can facilitate the automation of administrative tasks, allowing employees to focus on high-value activities that contribute to organizational goals (Mueller et al., 2017). Overall, the theoretical framework emphasizes the role of AI in providing actionable insights and metrics to support data-driven decision-making and performance optimization in the workplace.

2.2.4. Immediate Performance Feedback

The theoretical framework for immediate performance feedback through artificial intelligence (AI) revolves around leveraging AI-driven systems to provide timely and personalized feedback to employees, thereby enhancing performance management processes(Matt et al., 2021). AI-powered tools, equipped with real-time data analytics and natural language processing capabilities, can analyze employee performance metrics and interactions to deliver instant feedback on task completion, quality of work, and adherence to organizational goals (Piwowar-SULE, 2020). By providing immediate insights and recommendations, AI systems enable employees to course-correct and make necessary adjustments in real-time, fostering a culture of continuous improvement and development (Samarasinghe & Medis, 2020). Additionally, AI-driven feedback systems can tailor feedback to individual employee preferences and learning styles, enhancing engagement and receptivity to feedback(Mhlanga, 2021). Overall, the theoretical framework underscores the role of AI in facilitating proactive and actionable performance feedback, ultimately driving employee growth and organizational success.

2.2.5. Streamlining Payroll Automation

The theoretical framework for streamlining payroll automation through AI focuses on leveraging AI-driven technologies to optimize payroll processing and administration tasks within organizations(Fenwick et al., 2023). AI-powered payroll systems, equipped with machine learning algorithms and data analytics capabilities, can automate complex payroll calculations, tax deductions, and compliance reporting processes (Picinin et al., 2023). By analyzing historical payroll data and patterns, AI systems can identify anomalies, errors, and inconsistencies, thereby improving the accuracy and reliability of payroll processing (Shahzad et al., 2023). Additionally, AI-driven payroll automation tools can streamline administrative workflows, reducing manual intervention and minimizing the risk of human error (Shahzad et al., 2023). Furthermore, AI enables organizations to stay compliant with regulatory requirements and payroll regulations by continuously updating payroll systems and adjusting to changes in legislation (Bulut& Batur Dinler, 2023). Overall, the theoretical framework emphasizes the role of AI in enhancing efficiency, accuracy, and compliance in payroll administration processes, thereby enabling HR professionals to focus on strategic initiatives and value-added activities within the organization.

2.2.6. Influence on HR Digitalization

The theoretical framework for the influence of artificial intelligence (AI) on HR digitalization centers on leveraging AI-driven technologies to automate and optimize HR processes, thereby facilitating the digital transformation of HR functions within organizations(Sheikh et al., 2022). AI-powered systems, equipped with machine learning algorithms and natural language processing capabilities, can streamline various HR activities, including recruitment, onboarding, performance management, and employee engagement (Denisi & Murphy, 2017). By automating repetitive tasks, such as resume screening and candidate sourcing, AI enables HR professionals to focus on strategic initiatives and higher-value activities (Forner et al., 2020). Additionally, AI-driven analytics tools provide data-driven insights into workforce trends, employee sentiment, and organizational performance, enabling HR leaders to make informed decisions and drive organizational success (Treviño et al., 2006). Overall, the theoretical framework highlights the transformative role of AI in accelerating HR digitalization efforts and fostering innovation in HR practices.

2.2.7. Influence on Organizational Network Analysis

The theoretical framework for the influence of AI on organizational network analysis (ONA) revolves around leveraging AI-driven technologies to analyze and optimize communication patterns, collaboration dynamics, and network structures within organizations(Onesti, 2023; Shuck & Wollard, 2010). AI-powered ONA tools, equipped with advanced data analytics and network visualization capabilities, can analyze communication channels, email interactions, and social media activity to identify influential individuals, communication bottlenecks, and knowledge-sharing networks (Resende et al., 2023). By uncovering hidden patterns and insights, AI enables HR professionals and organizational leaders to enhance collaboration, facilitate knowledge transfer, and strengthen organizational networks (Asheq et al., 2022). Additionally, AI-driven interventions, such as targeted communication strategies and network mapping exercises, can promote diversity, inclusion, and innovation within organizational networks (Kumari & Yelkar, 2022; Rikku & Chakrabarty, 2013). Overall, the theoretical framework emphasizes the role of AI in providing actionable insights and recommendations to optimize organizational networks and drive strategic initiatives.

2.2.8. Influence on Organizational Design

The theoretical framework for the influence of AI on organizational design focuses on leveraging AI-driven technologies to optimize organizational structures, roles, and processes, thereby fostering agility, flexibility, and innovation within organizations(Mbore & Cheruiyot, 2017). AI-powered systems, equipped with predictive analytics and data-driven decision-making capabilities, can analyze workforce data, market trends, and customer insights to inform organizational design decisions (Abogsesa & Kaushik, 2017). By identifying skill gaps, talent needs, and emerging roles, AI enables HR professionals and organizational leaders to design adaptive and future-ready organizational structures (Mitchell et al., 2020). Additionally, AI-driven simulations and scenario planning tools can evaluate the impact of organizational changes and inform strategic decisions, enabling organizations to navigate complexity and uncertainty effectively (Bailey et al., 2017). Overall, the theoretical framework underscores the role of AI in driving organizational agility, resilience, and competitiveness through optimized organizational design and strategic alignment.

Table 1 outlines the variables identified in the study, encompassing various facets of human resource (HR) management influenced by artificial intelligence (AI) within the context of Industry 4.0.The proposed conceptual model in Figure 1 illustrates the interconnected relationships between these elements in HR management influenced by AI in the Industry 4.0 context.

Table 1 Identified Study's Variables

Variable	Explanation	Reference
Enhancement of Workplace Health and Safety	The measures and initiatives aimed at ensuring the well-being and safety of employees in workplace	(Fenwick et al., 2023; Vereycken et al., 2021)
Augmenting Employee Well-being	The overall satisfaction, mental health, and comfort level of employees within the organization	(Picinin et al., 2023; Tuomi, 2018)

Quantifying Employee Productivity	The efficiency of employees in completing tasks and achieving organizational goals	(Bujold et al., 2023; Wang et al., 2023)
Immediate Performance Feedback	The process of providing employees with constructive feedback on their performance	(Jatobá et al., 2019; Yang, 2022)
Streamlining Payroll Automation	The automation of payroll processing and administration tasks within the organization	(Rožman et al., 2023; Singh & Shaurya, 2021)
Influence on HR Digitalization	The degree to which HR processes and activities are digitized and automated using technology	(Alnamrouti et al., 2022; Goswami et al., 2023; Mueller et al., 2017)
Influence on Organizational Network Analysis	The analysis of communication patterns and collaboration dynamics within the organization	(Ammirato et al., 2023; Queiroz et al., 2022)
Influence on Organizational Design	The structure, roles, and processes within the organization, including adaptability and innovation	(Malik et al., 2022; Matt et al., 2021)

The hypotheses of the study revolve around the relationships between various factors and their impacts on HR digitalization, organizational network analysis (ONA), and organizational design within the context of Industry 4.0. Based on the variables and, following hypotheses are proposed;

H1a: Enhancement of Workplace Health and Safety positively influences HR Digitalization.
H2a: Augmenting Employee Well-being positively influences HR Digitalization.
H3a: Quantifying Employee Productivity positively influences HR Digitalization.
H4a: Immediate Performance Feedback positively influences HR Digitalization.
H5a: Streamlining Payroll Automation positively influences HR Digitalization.
H1b: Enhancement of Workplace Health and Safety positively impacts ONA.
H2b: Augmenting Employee Well-being positively impacts ONA.
H3b: Quantifying Employee Productivity positively impacts ONA.
H4b: Immediate Performance Feedback positively impacts Organizational Network Analysis (ONA).
H5b: Streamlining Payroll Automation positively impacts ONA.
H1c: Enhancement of Workplace Health and Safety positively influences Organizational Design.
H2c: Augmenting Employee Well-being positively influences Organizational Design.
H3c: Quantifying Employee Productivity positively influences Organizational Design.
H4c: Immediate Performance Feedback positively influences Organizational Design.
H5c: Streamlining Payroll Automation positively influences Organizational Design.

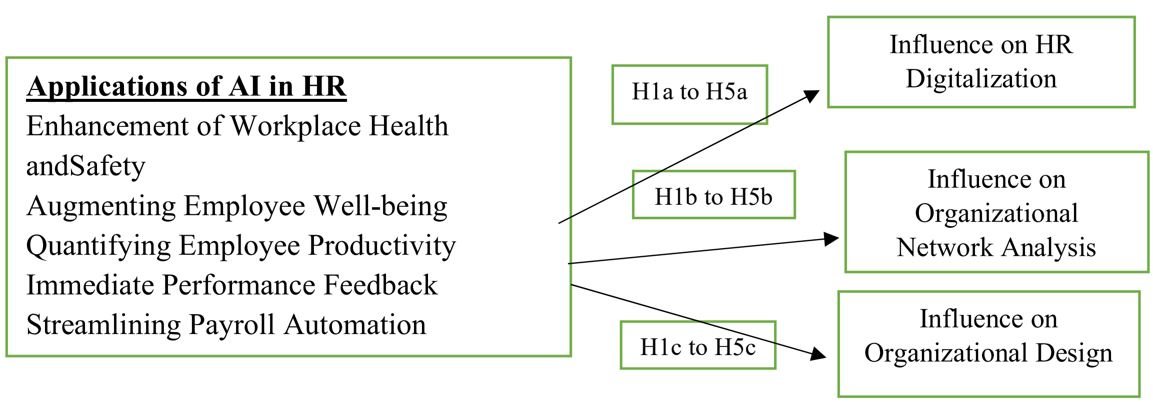

Fig. 1. Proposed conceptual model

3. Methodology

3.1. Research Design

This study employed a descriptive research design coupled with an analytical and empirical approach. Given the vast scope of data collection enabled by AI technology, this research design was deemed most appropriate to investigate the impact of AI on HR digitalization within Industry 4.0 (Murugesan et al., 2023).

3.2. Population and Sampling

The target population for this study comprised HR professionals across various sectors in Chennai and Bengaluru. These cities were selected for their representation of diverse industries, including IT, ITES, manufacturing, and services, providing a comprehensive sample pool. A multi-stage sampling technique was utilized, involving geographic selection, company ranking, and participant selection. A total of 360 surveys were distributed, out of which 271 met the review criteria, resulting in a response rate of 75%. The sample size of 271 was determined based on previous research and recommendations for SEM analysis (Yan et al., 2022).

3.3. Scale Development and Validation

The scales used in this study were developed by adapting relevant literature and subjected to rigorous testing for validity and reliability (Fornell & f. larcke, 1981). Confirmatory Factor Analysis (CFA) was employed to assess construct validity and reliability, with Composite Reliability (CR) values exceeding 0.7 and Average Variance Extracted (AVE) values surpassing 0.5, indicating strong convergent validity (Hair et al., 2019).

3.4. Data Collection

The study collected data through a structured questionnaire consisting of three sections: demographic questions, assessments of AI applications in HRM, and evaluations of Human Resource Agility. Responses were collected using a five-point Likert Scale.

3.5. Data Analysis

Primary statistical analysis of the acquired data was conducted using SPSS, while the proposed model underwent testing using PLS-SEM. The scales employed in this study were subjected to comprehensive testing for various validity and reliability measures, demonstrating satisfactory results and affirming their suitability for further investigation.

3.6. Validating SEM Assumptions

To ensure the correctness of the Structural Equation Modeling (SEM) assumptions, the researchers meticulously examined the skewness and kurtosis values of each variable, confirming their adherence to the acceptable range of -2 to +2, indicating normal distribution. Subsequently, maximum likelihood estimation, a fundamental concept in multivariate analysis, was employed to estimate model parameters. Listwise deletion was implemented to handle missing data, ensuring robustness in the analysis(Aboagye et al., 2016). With a final sample size of 271, exceeding the recommended minimum for SEM analysis, the researchers verified the appropriateness of the chosen model based on previous literature and theoretical underpinnings. Additionally, a validity check was conducted to assess the model's fit to the data, further strengthening the validity of the analysis.

The Table2 presents the reliability and validity assessment of the constructs of study, offering crucial insights into the robustness of the research model. Cronbach's alpha coefficient (α) is a measure of internal consistency reliability, indicating how closely related a set of items are as a group. With values ranging from 0.900 to 0.977 across the constructs, the coefficients surpass the recommended threshold of 0.7(Yan et al., 2022), affirming strong internal consistency within each construct. Additionally, Composite Reliability (CR) values, which assess the reliability of latent constructs in structural equation modeling, range from 0.894 to 0.965, exceeding the threshold of 0.7(Yan et al., 2022), further supporting the reliability of the measurement model.

Furthermore, the Average Variance Extracted (AVE) values, which gauge the amount of variance captured by the latent variables in relation to the measurement error, range from 0.503 to 0.777, surpassing the recommended threshold of 0.5(Yan et al., 2022). This suggests strong convergent validity, indicating that the constructs adequately measure the underlying theoretical concepts. The Table2 also provides insight into discriminant validity through comparisons of AVE with Maximum Shared Variance (MSV) and Average Shared Variance (ASV). The AVE values are higher than both MSV and ASV for all constructs, indicating discriminant validity among the constructs(Murugesan et al., 2023). Overall, the high reliability and validity values presented in the table affirm the robustness and validity of the constructs utilized in the study, lending credibility to the research findings and conclusions.

Table 2Reliability and validity of the constructs

Constructs	α	CR	AVE	MSV	ASV	HSI	EEC	EPM	APP	RTF	DHR	ONA	OD
Enhancement of Workplace Health and Safety	0.951	0.927	0.651	0.628	0.503	**0.806**							
Augmenting Employee Well-being	0.937	0.933	0.586	0.539	0.499	0.699	**0.765**						
Quantifying Employee Productivity	0.927	0.932	0.580	0.509	0.462	0.731	0.681	**0.763**					
Streamlining Payroll Automation	0.977	0.965	0.777	0.536	0.332	0.607	0.571	0.532	**0.882**				
Immediate Performance Feedback	0.900	0.894	0.522	0.508	0.379	0.683	0.591	0.532	0.554	**0.722**			
Influence on HR Digitalization	0.965	0.923	0.503	0.323	0.245	0.490	0.517	0.483	0.418	0.410	**0.709**		
Influence on 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**	
Influence on 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**

The Kaiser-Meyer-Olkin (KMO) statistic for this study was 0.872, surpassing the minimum recommended value of 0.6(Murugesan et al., 2023)**.** This indicates that the sample size is adequate and the data analysis is reliable. Bartlett's test of sphericity was employed to assess the accuracy of the correlation matrix. The test yielded a significance level of 0.001 (measured value 874.98), which is less than 0.0001. This result indicates a significant relationship between at least some variables. Thus, the assumption that the matrix relation is the identity matrix is not valid, implying that the variables are not orthogonal. A significance value below 0.05 suggests that conducting the test on the dataset is appropriate(Murugesan et al., 2023)**.**

4. Results and Discussion

4.1. Demographic Characteristics of Respondents

Figure 2 illustrates the demographic profile of the respondents. Among the participants, 51.7% were categorized as female, while the remaining 48.3% were male respondents, indicating a slight majority of female participants in the study. Concerning age distribution, a significant portion of respondents, accounting for 44.6%, fell within the 31 to 40 age bracket, followed by 32.8% in the 21–30 age group, suggesting substantial representation from individuals aged 31–40. Regarding educational attainment, approximately 65% of respondents held a bachelor's degree, while the rest possessed a master's degree. Notably, a predominant proportion of respondents were pursuing or had completed a bachelor's degree. In terms of organizational affiliation, the majority of participants, comprising 47.5%, belonged to the IT and ITES sector, followed by 29.5% from the Manufacturing sector, and 23% from the service sector.

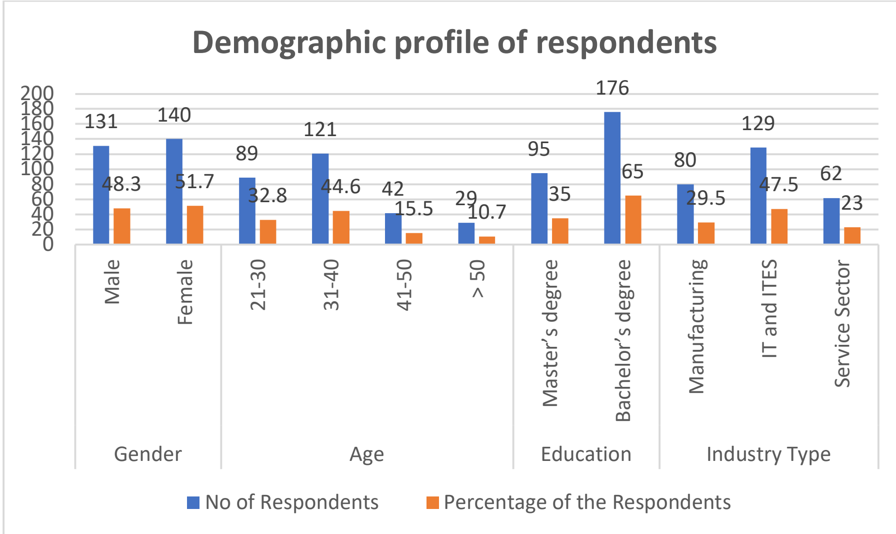

Fig. 2. Demographic profile of respondents

The fit indices in Table 3of the conceptual model indicate how well proposed model fits the observed data. In this study, the model demonstrates favorable fit indices, suggesting a good fit to the data. Firstly, the χ^2/df ratio (CMIN/DF) is 1.562, which is less than the recommended threshold of 3.0. A lower value indicates a better fit of the model to the data (Murugesan et al., 2023).Secondly, the Root Mean Square Error of Approximation (RMSEA) is 0.042, which falls below the recommended threshold of 0.08. This suggests that the model has a good fit, as RMSEA values closer to 0 indicate a better fit (Yan et al., 2022).Thirdly, the Comparative Fit Index (CFI) and Incremental Fit Index (IFI) both have values of 0.996, exceeding the recommended threshold of 0.90. These indices indicate a good fit of the proposed model to the data(Czarnowski & Pszczólkowski, 2020).Furthermore, the Goodness-of-Fit Index (GFI) and Adjusted Goodness-of-Fit Index (AGFI) have values of 0.992 and 0.867, respectively, both surpassing the recommended threshold of 0.90. Higher values of these indices indicate a better fit of the model to the data (Panda et al., 2023).Additionally, the Root Mean Square Residual (RMR) is 0.005, which is less than the recommended threshold of 0.08. This indicates a good fit of the model to the data, as lower values suggest better fit (Xin et al., 2022).Lastly, the Probability (P) value is 0.153, which exceeds the recommended threshold of 0.05. However, it's worth noting that this value alone does not determine model fit, and other fit indices should also be considered(Votto et al., 2021).Overall, the fit indices suggest that the proposed conceptual model fits the observed data well, as it meets or exceeds the recommended thresholds for various fit indices.

Table 3 Fit indices of conceptual model.

	CMIN/DF	RMSEA	CFI	IFI	GFI	AGFI	RMR	P-Value
Model	1.562	0.042	0.996	0.996	0.992	0.867	0.005	0.153
Recommended Standard	< 3.0	< 0.08	> 0.90	> 0.90	> 0.90	> 0.90	< 0.08	> 0.05

The results presented in Table 4 provide valuable insights into the relationships examined within the conceptual model, which is depicted in Figure 3. This model seeks to elucidate the connections between various factors—such as quantifying employee productivity, workplace health and safety enhancement, streamlining payroll automation, augmenting employee well-being, and immediate performance feedback—and their influences on HR digitalization, organizational network analysis (ONA), and organizational design within the context of Industry 4.0.

Starting with the influence on HR digitalization, the standardized coefficients reveal significant positive relationships between quantifying employee productivity (H3a), streamlining payroll automation (H5a), and augmenting employee well-being (H2a) with HR digitalization. These findings indicate that efforts to measure and enhance employee productivity, optimize payroll processes, and prioritize employee welfare play pivotal roles in driving the adoption and integration of digital technologies within HR functions.Conversely, the relationship between workplace health and safety enhancement and HR digitalization (H1a) exhibits a non-significant p-value (0.090), suggesting that while there may be a positive trend, the statistical evidence is not fully established.

Transitioning to the impact of these factors on organizational network analysis (ONA), the results unveil significant relationships between immediate performance feedback and ONA (H4b) and between employee well-being (H2b), workplace health and safety enhancement (H1b), quantifying employee productivity (H3b), and streamlining payroll automation (H5b) with ONA. These findings underscore the importance of immediate feedback, employee well-being, safety measures, productivity measurement, and payroll automation in shaping organizational network dynamics.

Moreover, the model explores the influence of employee well-being (H2c), workplace health and safety enhancement (H1c), quantifying employee productivity (H3c), streamlining payroll automation (H5c), and immediate performance feedback (H4c) on organizational design. The results indicate significant negative relationships between employee well-being, quantifying employee productivity, and streamlining payroll automation with organizational design, suggesting that prioritizing these factors may necessitate adjustments to organizational structures and configurations.

In summary, the conceptual model and corresponding results provide a comprehensive understanding of the multifaceted relationships between various factors and their impacts on HR digitalization, ONA, and organizational design in the context of Industry 4.0. These insights can inform strategic decision-making processes within organizations aiming to navigate and thrive in the rapidly evolving digital landscape.

Table 4 Results of the conceptual model

Hypothesis	Path	Standardized Coefficient	*P* -value	R^2
H3a	Quantifying Employee Productivity → Influence on HR Digitalization	.422	0.000	0.508
H1a	Enhancement of Workplace Health and Safety→ Influence on HR Digitalization	.109	0.090	
H5a	Streamlining Payroll Automation → Influence on HR Digitalization	.261	0.000	
H2a	Augmenting Employee Well-being → Influence on HR Digitalization	.238	0.000	
H4a	Immediate Performance Feedback→ Influence on HR Digitalization	-.084	.247	
H4b	Immediate Performance Feedback→ Impact of Organizational Network Analysis (ONA)	-.278	0.000	0.772
H2b	Augmenting Employee Well-being → Impact of Organizational Network Analysis (ONA)	.386	0.000	
H1b	Enhancement of Workplace Health and Safety→ Impact of Organizational Network Analysis (ONA)	.660	0.000	
H3b	Quantifying Employee Productivity → Impact of Organizational Network Analysis (ONA)	.180	0.000	
H5b	Streamlining Payroll Automation → Impact of Organizational Network Analysis (ONA)	.194	0.000	
H2c	Augmenting Employee Well-being → Influence on Organizational Design	-.514	0.000	0.440
H1c	Enhancement of Workplace Health and Safety → Influence on Organizational Design	.339	0.000	
H3c	Quantifying Employee Productivity → Influence on Organizational Design	-.222	0.000	
H5c	Streamlining Payroll Automation → Influence on Organizational Design	-.129	.064	
H4c	Immediate Performance Feedback→ Influence on Organizational Design	.630	0.000	

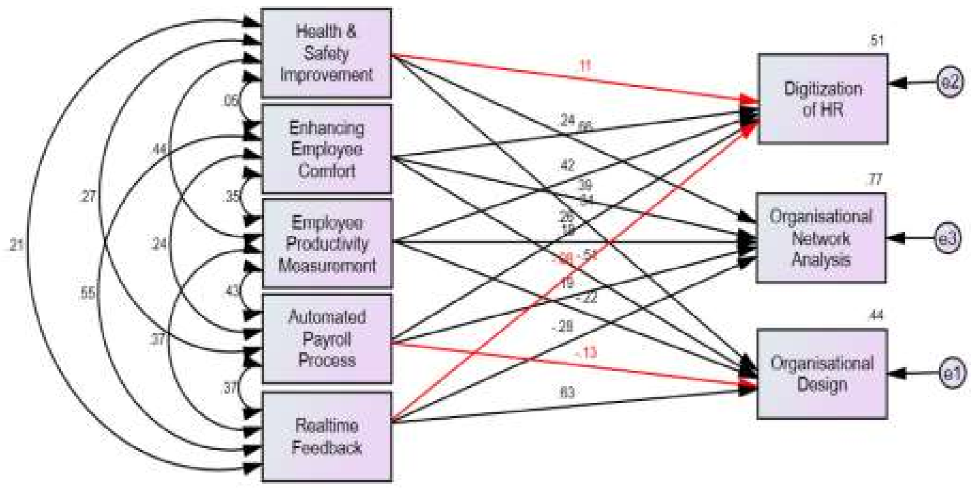

Figure 3.HypothesizedConceptualModel.

5. Discussion

Based on the findings of the study, which are consistent with existing literature, several significant implications and discussions emerge regarding the profound impact of artificial intelligence (AI) on human resources (HR) within the emergence of Industry 4.0.

First and foremost, the study reaffirms the assertions made in prior research by showcasing that AI technologies wield a substantial influence across various facets of HR operations. These encompass critical areas such as recruitment, talent management, learning and development, performance management, workplace safety, and payroll administration. In line with established literature, AI-powered tools streamline these processes, markedly enhancing operational efficiency and bolstering decision-making capabilities within HR departments(Rožman et al., 2023; Xin et al., 2022).

Furthermore, the study emphasizes the pivotal role of agility within HR functions amidst the dynamic landscape of Industry 4.0. This agility encompasses the capacity to swiftly adapt to technological advancements, shifting workforce dynamics, and evolving organizational needs. The study findings indicate that AI adoption serves as a catalyst for enhancing HR readiness and adaptability, equipping organizations with the agility needed to effectively address these evolving challenges (Panda et al., 2023; Tuomi, 2018).

Moreover, the study sheds light on the potential of AI to significantly enhance employee well-being and safety in the workplace. AI-driven systems exhibit the capability to proactively identify potential hazards, analyze employee sentiment, and deliver personalized support, thereby fostering a safer and more supportive work environment. These observations resonate with the theoretical framework proposed in the literature, underscoring the instrumental role of AI in augmenting workplace health and safety measures while bolstering employee well-being(Alnamrouti et al., 2022; Czarnowski & Pszczólkowski, 2020).

Additionally, the study unveils the profound impact of AI on organizational network analysis (ONA) and organizational design. AI-powered ONA tools empower HR professionals and organizational leaders with the means to analyze communication patterns, collaboration dynamics, and network structures within organizations. This facilitates the optimization of collaboration, promotion of knowledge-sharing, and design of adaptive organizational structures. These insights corroborate previous research, which has highlighted the transformative potential of AI in revolutionizing organizational network analysis and design paradigms (Bulut & Batur Dinler, 2023; Picinin et al., 2023; Shahzad et al., 2023).

Based on above, the findings of this study significantly contribute to the existing body of literature by furnishing empirical evidence of AI's transformative influence on HR practices within the context of Industry 4.0. By corroborating and extending prior research, this study underscores the critical importance of AI adoption in enhancing HR quality, organizational efficiency, and workforce well-being in the digital age. These insights carry profound implications for HR professionals, organizational leaders, policymakers, and researchers, emphasizing the imperative of continued investment in AI technologies and the strategic development of HR initiatives to effectively navigate the challenges and capitalize on the opportunities presented by Industry 4.0.

Theoretical Implications

This study enriches theoretical understanding by corroborating and extending existing frameworks regarding the transformative influence of AI on HR practices within context of Industry 4.0. By employing a rigorous research design and comprehensive data analysis, it validates prior research findings while also shedding new light on the multifaceted ways in which AI technologies reshape HR operations. The study emphasizes the strategic importance of AI adoption for enhancing HR efficiency, agility, and organizational performance, thus contributing to advancement of theoretical models in field.

Managerial Implications

From a managerial perspective, findings of this study offer actionable insights for HR practitioners and organizational leaders. By highlighting the strategic role of AI in HR processes, decision-making, and workplace safety, the study underscores the need for proactive AI adoption initiatives within organizations. Managers can leverage AI-driven systems to streamline HR processes, optimize decision-making, and foster a safer work environment, thereby enhancing organizational effectiveness and resilience in the face of dynamic digital landscapes. Additionally, the study emphasizes the importance of strategic AI integration to promote employee well-being and optimize collaboration dynamics, aligning HR practices with organizational goals and objectives.

6. Conclusion

The conclusions of the study highlight the significant impact of AI onHR practices within the framework of Industry 4.0. Through a thorough examination of various factors and their interrelationships, several key findings emerge. Firstly, the study highlights the positive association between efforts to measure and enhance employee productivity, streamline payroll processes, and prioritize employee well-being with HR digitalization. These insights emphasize the strategic importance of AI adoption in driving the integration of digital technologies within HR functions, ultimately enhancing operational efficiency and decision-making capabilities.

Moreover, the study reveals the significant influence of AI on organizational network analysis (ONA). Factors such as immediate feedback, employee well-being, safety measures, productivity measurement, and payroll automation play crucial roles in shaping organizational network dynamics. AI-powered ONA tools empower HR professionals and organizational leaders to analyze communication patterns and collaboration dynamics, facilitating the optimization of collaboration and the promotion of knowledge-sharing within organizations. This highlights the transformative capacity of AI in revolutionizing traditional organizational network analysis paradigms.

Additionally, the study sheds light on the impact of AI on organizational design. While factors such as employee well-being, quantifying employee productivity, and streamlining payroll automation exhibit significant negative relationships with organizational design, the findings suggest that prioritizing these factors may require adjustments to organizational structures and configurations. This emphasizes the need for organizations to adapt their design frameworks to align with the evolving needs of Industry 4.0, where AI plays a central role in driving organizational efficiency and resilience.

Furthermore, the study emphasizes strategic importance of AI adoption for enhancing HR efficiency, agility, and organizational performance. AI-powered tools streamline HR processes, optimize decision-making, and foster a safer work environment, ultimately contributing to organizational effectiveness and resilience in the face of dynamic digital landscapes. From a managerial perspective, these findings offer actionable insights for HR practitioners and organizational leaders, emphasizing the strategic role of AI in HR processes, decision-making, and workplace safety.

In conclusion, the study provides empirical evidence of AI's transformative influence on HR practices within the framework of Industry 4.0. By corroborating and extending prior research, these insights underscore the critical importance of AI adoption in enhancing HR quality, organizational efficiency, and workforce well-being in the digital age. These findings have profound implications for HR professionals, organizational leaders, policymakers, and researchers, highlighting the imperative of continued investment in AI technologies and the strategic development of HR initiatives to effectively navigate the challenges and capitalize on the opportunities presented by Industry 4.0.Limitations of the study include a focus on specific industries and regions, warranting future research to explore broader contexts.

Data Availability Statement

The data utilized in this study are available from corresponding author based upon reasonable request.

Declaration

The authors declare that there are no conflicts of interest regarding the publication of this research.

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