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ENHANCING EMPLOYEE EFFICIENCY AND PERFORMANCE IN INDUSTRY 5.0 ORGANIZATIONS THROUGH ARTIFICIAL INTELLIGENCE INTEGRATION

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ABSTRACT

The paper explores the transformative effects of Industry 5.0, a data-driven economy, and the imperative adoption of Artificial Intelligence (AI) driven systems across all organizational levels. It emphasizes the urgent need for comprehensive transformation, extending to Human Resource Management (HRM). Industry 5.0 presents significant challenges, necessitating strategic HRM strategies involving skill enhancements and AI-assisted knowledge management. A central focus is the profound impact of AI-driven innovations on organizational efficiency, employee efficacy, and productivity. AI rapidly acquires and processes data, providing organizations with prescriptive and predictive insights, enabling them to navigate potential future scenarios effectively. These insights can be leveraged to enhance productivity, engage employees, and facilitate organizational growth. Beyond HRM, the paper recognizes AI's influence on marketing and sales strategies in Industry 5.0. AI-driven advancements revolutionize customer engagement and personalization. AI-powered chatbots, for example, offer tailored interactions that elevate customer satisfaction and engagement. AI's data analytics capabilities empower businesses to craft highly targeted marketing campaigns, enhancing service quality and response times, yielding favourable marketing and sales outcomes. Furthermore, AI-driven Chatbot tools such as Chorus and GrowthBot play a pivotal role in recording and analyzing sales conversations, offering valuable insights into customer behavior. This provides informed decision-making and accelerates lead conversion. AI's rapid data processing capabilities enable organizations to refine marketing and sales strategies, boosting their effectiveness and financial results. To conclude, the research highlights AI's transformative impact across organizational facets, including HRM, marketing, and sales. Embracing AI-driven processes and systems offers a competitive edge by enhancing employee productivity and revolutionizing customer engagement and sales strategies. This comprehensive approach is crucial for thriving in the data-driven landscape of Industry 5.0, where harnessing the power of AI is paramount for success.

KEY WORDS: Artificial Intelligence, Chatbot, Industry 5.0, Innovation, Marketing, Human Resource Management, Productivity

INTRODUCTION

The integration of Artificial Intelligence (AI) into Industry 5.0 organizations represents a paradigm shift in the way businesses operate [1]. AI's unique attributes, such as the ability to learn from manufacturing data, play a pivotal role in enhancing various aspects of efficiency and performance in these organizations [2]. This article explores the multifaceted impact of AI on Industry 5.0, shedding light on its potential to revolutionize the workplace [3].

AI's Role in Industry 5.0: Industry 5.0 is characterized by the coexistence of humans, robots, intelligent machines, and advanced technology [1]. It builds upon the pillars of automation and efficiency established in Industry 4.0 but adds a critical human touch to the equation. In this context, AI becomes a transformative tool that holds great promise for forward-thinking managers. AI-driven technologies are not only the backbone of the Internet of Things (IoT) in Industry 5.0 but also enable precise production automation and critical thinking applications [2].

Impact on Employee Productivity and Decision-Making: AI's influence on Industry 5.0 is profound. It enhances productivity, the economy, and overall business performance. AI-driven automation reduces labour costs and increases efficiency, making organizations that fail to adapt to this new model quickly become outdated [3]. For instance, Deloitte provides productivity analytics tools powered by AI to help identify areas where labour expenses are excessive, thus removing barriers to productivity. Real-time AI analysis can bridge the gap between disengaged employees and their jobs, with 51% of U.S. employees reported as feeling disconnected [4]. AI's data collection, storage, and analysis capabilities streamline decision-making, providing predictive and prescriptive insights, ultimately improving employee productivity [5].

Transforming Recruitment, Onboarding, and Internal Communications: Industry 5.0 introduces a frontier where intelligent factories interact with both humans and robots, emphasizing the importance of effective communication [6]. AI-powered solutions transform recruitment, onboarding, and internal communications. Applicant profiles can be pre-screened using AI, enhancing the efficiency of the hiring process [7]. AI service desks like atSpoke reduce interruptions from repetitive inquiries, allowing team members to focus on their tasks [8]. AI's ability to provide automatic translations in near-real-time dialogues, as seen in Skype Translator, facilitates global communication. Marketing, sales, and customer service benefit from AI-powered chatbots, offering personalized interactions that enhance service quality and response time [9]. AI-powered chatbots, for example, offer tailored interactions that elevate customer satisfaction and engagement. AI's data analytics capabilities empower businesses to craft highly targeted marketing campaigns, enhancing service quality and response times, yielding favourable marketing and sales outcomes [10]. Furthermore, AI-driven tools such as Chorus and GrowthBot play a pivotal role in recording and analyzing sales conversations, offering valuable insights into customer behavior [11]. This provides informed decision-making and accelerates lead conversion. AI's rapid data processing capabilities enable organizations to refine marketing and sales strategies, boosting their effectiveness and financial results [12].

Revolutionizing Business Data Analytics and Security: AI-driven data analytics is essential in Industry 5.0 [13]. Domo, for example, leverages AI to centralize company data in the cloud, predicting critical business performance indicators without requiring a data scientist's intervention [14].

AI also plays a pivotal role in cybersecurity, detecting and preventing threats. Innovative solutions like Spark Cognition's Deep Armor guard against malware attacks, while Exabeam identifies insider threats. AI's potential to mimic the human intelligence system in dealing with cyber threats is a promising development [15].

Corporate Training and Development: Continuous learning is crucial in Industry 5.0, and AI technologies enhance corporate training programs [16]. AI-driven augmented and virtual reality tools, such as those developed by Honeywell, improve training effectiveness [17]. Adaptive learning experiences empower employees to develop their skills and contribute to organizational success [18].

Streamlining Business Processes: AI-driven automation streamlines business operations, reducing manual effort and errors [19]. Platforms like Kissflow expedite operations and optimize processes across distributed teams [20]. Machine learning models enhance demand forecasting, inventory management, and production optimization, leading to increased efficiency and cost savings [21].

Future Trends in AI: The future of AI holds exciting possibilities. Knowledge learning engineering using language processing is improving AI's ability to interpret human language, making chatbots increasingly sophisticated [22]. AI's capability to evaluate real-world events accurately through simulations is on the rise. Smart process automation and labour arbitrage will continue to evolve, reshaping work processes [23]. AI's progress in human-machine interaction, recognizing emotions in human voices and written words, will lead to more intuitive interactions [24].

In conclusion, AI's integration into Industry 5.0 organizations is transformative, impacting efficiency, productivity, and performance across various domains [25]. As AI technologies continue to evolve, their role in shaping the future of work and business performance will become even more significant. Organizations that embrace AI stand to gain a competitive advantage in the evolving landscape of Industry 5.0 [26].

REVIEW OF LITERATURE

A study in human resources offered a comprehensive exploration of the integration of artificial intelligence (AI) into the domain of human resource management (HRM). The study's three-pronged approach which delves into various facets of this integration. Firstly, it highlights the potential of AI-assisted decision-making in HRM, emphasizing how it can alleviate HR staff from routine tasks, allowing them to focus on more strategic endeavours. Secondly, the study underscores the transformation of HR departments within organizations, emphasizing their shift from reactive problem solvers to proactive strategic decision-makers, facilitated by AI. Finally, it delves into the financial implications of AI adoption in HRM, emphasizing the need for proper implementation strategies, including staff reskilling and transparency policies, to ensure AI enhances trust and commitment in the workplace [27].

Another study discussed the profound impact of AI on the energy sector, highlighting its potential to enhance efficiency, energy management, transparency, and the utilization of renewable energy sources. The study emphasizes the role of AI in optimizing power system equipment monitoring, data analysis, and resource allocation in the energy industry. By securely supplying renewable and cost-effective electricity from diverse sources, AI empowers utilities to meet consumer needs more efficiently [28].

Recent research investigated the dynamic effects resulting from the integration of AI with other key technologies, creating economies of scale and scope for businesses. The study underscores the importance of AI in enhancing organizational performance and competitiveness [29].

Some researchers explored the multifaceted impact of AI adoption, identifying both positive and negative consequences. The study highlights concerns related to information security, data privacy, and employment stability, while also recognizing the benefits, including job-related flexibility, creativity, and improved overall job performance [30].

The study investigated the influence of AI on innovation control, emphasizing the limitations of traditional human-focused innovation control procedures. It reveals that AI introduces a more systematic approach to innovation management, leveraging machine learning algorithms to identify new opportunities and overcome information processing limitations [31].

Another recent investigation analyzed the impact of AI on labour productivity, particularly its influence on service industries and small and medium enterprises (SMEs). The research highlights that AI-based projects have a positive effect on labour productivity, underscoring the importance of adaptability and the rapid introduction of AI-based applications [32].

This researcher explored the immediate and disruptive applications of AI in management, emphasizing its significance for organizational effectiveness and competitiveness [33].

This study discussed the potential positive outcomes of automation and innovation on labour productivity, suggesting that innovative changes can lead to increased efficiency [34].

A scientist proposed the use of AI approaches in medical science and medicine, highlighting their potential as diagnostic and predictive tools for various illnesses [35].

A team of scientists suggested that AI can enhance profitability by improving the accuracy of predictions and recombining existing innovations [36].

This study presented a framework for using AI in digital transformations, incorporating knowledge in leadership, data, integration, intelligence, agility, and teamwork [37].

Another study investigated the impact of AI integration in business processes, focusing on innovation, research, market development, and shifts in business models. Their research model considers innovation, knowledge, and entrepreneurship as key factors [38]

A team of researchers examined the influence of AI on employment, incomes, and growth. They emphasize that AI can enhance productivity but also has distributive implications [39].

A scholar discussed the integration of AI into various jobs and highlights the complementary role of AI in augmenting human capabilities [40].

Later, another study investigated the impact of AI on innovation, particularly its role in enhancing efficiency and reshaping the innovation process [41].

A team of two researchers assessed the impact of AI on employment, incomes, and growth, emphasizing its potential to increase productivity in various industries [42].

Few researchers suggested that AI, particularly machine learning, is a critical technology of the digital era, capable of enhancing productivity and efficiency [43].

A short literature review study analyzed the influence of AI and robotics on labour and productivity, emphasizing the need for structured data collection and analysis [44].

Previously a researcher discussed supply chain performance in terms of efficiency, effectiveness, and agility, highlighting the role of AI in enhancing resource and output performance [45].

Similarly, another team of researchers discussed the potential for AI-driven technological change to polarize wages and automate tasks, impacting labour markets [46].

Finally, this research suggested that educational advancement and technological change are interconnected, driving economic growth [47].

These studies collectively underscore the multifaceted impact of AI across various sectors, emphasizing its potential to enhance productivity, drive innovation, and reshape industries while also raising important questions about its societal and economic implications [48].

METHODOLOGY

The sample design process for this research aimed to create a representative sample of global employees in organizations. The purposive sampling technique was applied to select highly cited and reputable research papers focusing on the impact of AI-driven innovation on employee efficiency and performance [49].

Sample Size: More than 30 highly cited and well-reputed research papers from last 20 years (2002-2023), focusing upon the impact artificial intelligence driven innovation on efficiency and performance of employees engaged in Organizations preliminary in Industry globally were selected [50]. After critical qualitative in-depth analysis of selected research papers, 13 CIs (Competency Indicators) were identified for further analysis, namely: *Level of Automation, Data and Content, Level of Innovativeness, Work Quality, Work Productivity, Level of AI adoption, Potential Capacity, Economic Outcome, Knowledge Stock, Firm Size, Digital Transformation, Agility and Teaming*

Tools & Techniques: Factor Analysis was employed to reduce the dimensionality of the 13 CIs, utilizing the main component extraction approach with Varimax rotation [51]. This technique condenses numerous variables into a more manageable set, facilitating the interpretation of their relationships [52]. The resulting factors were renamed based on their collective representation, allowing for a more comprehensive understanding of how they influence the impact of AI-driven innovation on employees' efficiency and performance [53].

RESULTS

As a first step of factor analysis, the correlation matrix was obtained (see Figure 1).

Figure 1: Correlation Matrix based in Principal Component Factor Analysis

Correlation Matrix[a]

	Level_of_Automation	Data_and_Content	Level_of_Innovativeness	Work_Quality	Work_Productivity	Level_of_AI_adoption	Potential_Capacity	Economic_Outcome	Knowledge_Stock	Firm_Size	Digital_Transformation	Agility	Teaming
Level_of_Automation		**0.551**	**0.383**	**0.471**	0.231	-0.261	**0.353**	**0.331**	-0.056	-0.06	0.073	0.148	-0.11
Data_and_Content	**0.551**		**0.375**	**0.507**	0.086	-0.009	0.174	0.286	-0.201	0.159	0.266	0.206	-0.231
Level_of_Innovativeness	**0.383**	**0.375**		0.138	0.422	-0.181	0.02	0.17	-0.017	0.293	0.055	0.199	0.107
Work_Quality	**0.471**	**0.507**	0.138		0.225	0.184	**0.371**	0.001	-0.137	-0.156	**0.499**	**0.454**	0.02
Work_Productivity	0.231	0.086	0.422	0.225		-0.279	**0.452**	**0.32**	0.269	-0.026	-0.052	-0.185	-0.102
Level_of_AI_adoption	-0.261	-0.009	-0.181	0.184	-0.279		-0.215	-0.027	-0.089	0.161	0.202	0.151	0.087
Potential_Capacity	**0.353**	0.174	0.02	0.371	**0.452**	-0.215		0.029	-0.059	-0.222	0.142	-0.026	-0.263
Economic_Outcome	**0.331**	0.286	0.17	0.001	**0.32**	-0.027	0.029		0.183	0.288	0.083	-0.02	0.024
Knowledge_Stock	-0.056	-0.201	-0.017	-0.137	0.269	-0.089	-0.059	0.183		-0.038	0.164	0.082	**0.392**
Firm_Size	-0.06	0.159	0.293	-0.156	-0.026	0.161	-0.222	0.288	-0.038		0.043	0.167	0.031
Digital_Transformation	0.073	0.266	0.055	0.499	-0.052	0.202	0.142	0.083	0.164	0.043		**0.462**	**0.312**
Agility	0.148	0.206	0.199	0.454	-0.185	0.151	-0.026	-0.02	0.082	0.167	**0.462**		0.222
Teaming	-0.11	-0.231	0.107	0.02	-0.102	0.087	**-0.26**	0.024	**0.392**	0.031	0.312	0.222	

Source: Authors self-data computation using SPSS version 25 and R studio

Bold red colour shows significant correlation (p values <0.05). Correlation values: r>**0.5** were considered as **high correlation**, correlation values between r=**0.3-0.5** were considered as **moderate correlation** and values with r<**0.3** were considered as **low correlation** [54]. The obtained results from the correlation matrix analysis reveal the following relationships among key performance indicators (KPIs):

1. "Level of Automation" exhibits a high positive correlation with "Data & Content" and a medium correlation with "Level of Innovativeness," "Work Quality," "Potential Capacity," and "Economic Outcome." Notably, it demonstrates the strongest positive correlation with five other critical indicators [55].
2. "Data & Content" displays a high positive correlation with "Level of Automation" and "Work Quality," along with a medium correlation with "Level of Innovativeness" [56].
3. "Level of Innovativeness" demonstrates a medium correlation with "Level of Automation" and "Data & Content" [57].
4. "Work Quality" shows a high positive correlation with "Data & Content" and a medium correlation with "Level of Innovativeness" [58].
5. "Work Productivity" exhibits a medium correlation with "Potential Capacity" and "Economic Outcome" [59].
6. "Level of AI Adoption" and "Firm Size" do not display any significant correlations with other KPIs [60].
7. "Potential Capacity" demonstrates a medium correlation with "Level of Automation," "Work Quality," and "Work Productivity." It also exhibits a low negative correlation with "Teaming" [61].
8. "Economic Outcome" displays a medium correlation with "Level of Automation" and "Work Productivity" [62].
9. "Knowledge Stock" exhibits a medium correlation with "Teaming" [63].
10. "Digital Transformation" demonstrates a medium correlation with "Work Quality" and "Agility."
11. "Teaming" shows a medium correlation with "Knowledge Stock" and "Digital Transformation" [64].

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These results provide valuable insights into the interrelationships among various key performance indicators within the analyzed dataset, shedding light on the complex dynamics within the studied context.

The Kaiser-Meyer-Olkin Measure (KMO) assessing the adequacy of sampling should surpass the threshold of 0.50 (as depicted in Table 1). A KMO value below 0.5 would signify the inability to derive discernible and dependable factors [65]. A KMO exceeding 0.5 signifies that the model has yielded factors that are both distinct and dependable [66]. In this instance, the KMO stands at 0.513, affirming that our model has generated factors that are distinct and reliable [67].
Regarding Bartlett's Test of Sphericity, the obtained value was 0.017 (with a significance level of $p < 0.05$). This outcome leads to the conclusion that the 13 key performance indicator (KPI) variables exhibit a pattern of interrelationships [68].

Table1: Kaiser-Meyer-Olkin Measure of Sampling Adequacy and Bartlett's Test of Sphericity

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**.513**
Bartlett's Test of Sphericity	Approx. Chi-Square	106.829
	df	78
	Sig.	**.017**

Source: Authors self-data computation using SPSS version 25

It has been observed that all the 13 CIs were able to explain the extraction of factors obtained (see Table 2).

Table 2: Communality Extraction

Communalities		
	Initial	Extraction
Level_of_Automation	1.000	.669
Data_and_Content	1.000	.722
Level_of_Innovativeness	1.000	.512
Work_Quality	1.000	.842
Work_Productivity	1.000	.665
Level_of_AI_adoption	1.000	.421
Potential_Capacity	1.000	.654
Economic_Outcome	1.000	.548
Knowledge_Stock	1.000	.746
Firm_Size	1.000	.610
Digital_Transformation	1.000	.687
Agility	1.000	.602
Teaming	1.000	.653
Extraction Method: Principal Component Analysis.		

Source: Authors self-data computation using SPSS version 25

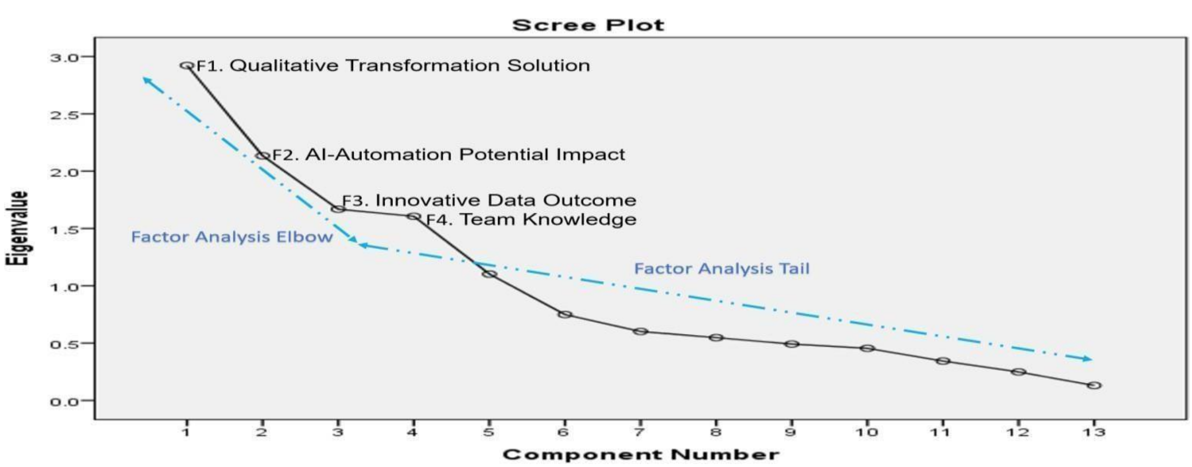
It has been observed that 4 factors extracted from factor analysis, contributed to 64% explanation of variance for the developed factor analysis model (see Table 3).

Table 3: Total Variance Explained by 4 Factors

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.922	22.478	22.478	2.922	22.478	22.478	2.421	18.623	18.623
2	2.134	16.415	38.893	2.134	16.415	38.893	2.215	17.040	35.663
3	1.668	12.831	51.724	1.668	12.831	51.724	1.924	14.800	50.464
4	1.606	12.356	64.081	1.606	12.356	64.081	1.770	13.617	64.081
5	1.102	8.480	72.561						
6	.749	5.762	78.323						
7	.601	4.626	82.949						
8	.548	4.212	87.162						
9	.492	3.782	90.943						
10	.455	3.500	94.443						
11	.344	2.643	97.086						
12	.249	1.912	98.998						
13	.130	1.002	100.000						
Extraction Method: Principal Component Analysis.									

Source: Authors self-data computation using SPSS version 25

Figure 2: Scree plot showing loading of 4 clear factors from 13 CIs



Source: Authors self-data computation using SPSS version 25

Screen plot (see Figure 2) clearly indicated extraction and loading of 4 prominent factors through factor analysis [69].

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Table 4: Rotated Component Matrix obtained through factor analysis

Rotated Component Matrix[a]				
	Component			
	F1 Qualitative Transformation Solution	F2 AI-Automation Potential Impact	F3 Innovative Data Outcome	F4 Team Knowledge
Level_of_Automation	.342	.541	.437	-.262
Data_and_Content	.466	.207	.529	-.426
Level_of_Innovativeness	.150	.048	.695	-.066
Work_Quality	.851	.279	-.008	-.202
Work_Productivity	-.061	.786	.084	.189
Level_of_AI_adoption	.318	.554	-.109	-.022
Potential_Capacity	.257	.712	-.177	-.223
Economic_Outcome	-.046	.292	.645	.212
Knowledge_Stock	-.016	.228	.029	.832
Firm_Size	-.083	-.353	.690	.055
Digital_Transformation	.777	-.050	.012	.283
Agility	.706	-.235	.166	.142
Teaming	.238	-.218	.033	.740
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a]				
a. Rotation converged in 10 iterations.				

Source: Authors self-data computation using SPSS version 25

Through the application of a rotated component matrix, four distinct factors have emerged and are outlined in Table 4. Here, we provide detailed descriptions of each factor, along with the competency indicators (CIs) that have been loaded onto them:

Factor 1 (F1) - Qualitative Transformation Solution: This factor encompasses Work Quality, Digital Transformation, and Agility as its constituent components [70].

Factor 2 (F2) - AI-Automation Potential Impact: Factor 2 comprises Level of Automation, Work Productivity, Level of AI Adoption, and Potential Capacity as the CIs that have been loaded onto it [71].

Factor 3 (F3) - Innovative Data Outcome: Factor 3 includes Data and Content, Level of Innovativeness, Economic Outcome, and Firm Size as the CIs that are associated with it [72].

Factor 4 (F4) - Team Knowledge: The fourth factor, Factor 4, is characterized by the inclusion of Knowledge Stock and Teaming as the CIs that have been loaded onto it [73].

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DISCUSSION

Based on the outcomes derived from the correlation matrix and subsequent factor analysis, it is evident that Competency Indicators (CIs), namely "Level Automation," "Data & Content," and "Potential capacity," exhibit the highest degree of positive correlation with the remaining CIs, indicating a robust association [74].

The factor analysis results further unveil the presence of four distinct factors, each contributing significantly to the overall variance of factor loadings. Factor 1, labeled "Qualitative Transformation Solution," accounts for 18.623% of the variance in factor loadings, encompassing Competency Indicators such as "Work Quality," "Digital Transformation," and "Agility." This suggests that the flexibility introduced by agility and positive digital transformation in the workplace fosters an environment conducive to enhanced work quality [75].

Factor 2, denoted as "AI-Automation Potential Impact," explains 17.040% of the variance in factor loadings and includes CIs like "Level of Automation," "Work Productivity," "Level of AI adoption," and "Potential Capacity." This factor indicates that increased AI adoption and automation levels in official tasks positively correlate with heightened work productivity, time and cost savings, ultimately enhancing an organization's overall potential and capacity [68].

Factor 3, labeled "Innovative Data Outcome," captures 14.800% of the variance in factor loadings, encompassing CIs such as "Data and Content," "Level of Innovativeness," "Economic Outcome," and "Firm Size." It suggests that a high degree of innovation and the presence of creative web content contribute significantly to a firm's growth and higher economic returns. In the realm of marketing, the application of AI chatbots has emerged as a transformative tool. These chatbots facilitate personalized customer interactions, enhancing satisfaction and engagement. Through advanced data analytics, AI chatbots enable tailored marketing campaigns, aligning products and services with individual customer preferences [69].

Factor 4, designated as "Team Knowledge," accounts for 13.617% of the variance in factor loadings and includes CIs like "Knowledge Stock" and "Teaming." This factor underscores the significance of knowledgeable teams and a persistent learning attitude among employees in enhancing overall work productivity [72].

These four factors, derived from the 13 CIs, collectively exert a cumulative effect on the growth and productivity of Industry 5.0 organizations, ultimately resulting in improved work productivity and higher economic returns [73].

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CONCLUSION

In the ever-evolving landscape of Industry 5.0, AI is at the forefront of transformation, revolutionizing workplaces and reshaping the future of work. The study explored the critical factors contributing to the growth and productivity of Industry 5.0 organizations, identifying a range of significant elements such as automation, data utilization, work quality, digital transformation, and AI adoption. Four key factors— Qualitative Transformation Solution, AI-Automation Potential Impact, Innovative Data Outcome, and Team Knowledge— were found to synergize, collectively driving the growth and productivity of Industry 5.0 organizations. AI's role in this transformation is pivotal, making workplaces more humane and productive. While automation takes care of certain tasks, the human aspect of work becomes increasingly vital. AI technologies not only enhance productivity but also create new job opportunities, allowing employees to focus on more human-centric aspects of their roles, such as customer service, engagement, and workplace culture. Moreover, AI's influence extends to marketing, where chatbots play a significant role. AI-powered chatbots are being widely adopted in marketing strategies, delivering personalized interactions that boost customer satisfaction and engagement. AI's data analytics capabilities enable businesses to craft highly targeted marketing campaigns, resulting in higher economic returns. In the context of Industry 5.0's data-driven economy, the study underscores the need for a shift toward AI-driven systems and processes at all organizational levels. This shift necessitates comprehensive transformation and strategic human resource management (HRM) strategies, including skill enhancements and AI-assisted knowledge management.

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