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A STUDY ON IMPACT OF ARTIFICIAL INTELLIGENCE FACTORS ON LABOUR FORCES IN MANUFACTURING INDUSTRY

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Abstract

The adoption of Artificial Intelligence (AI) technology has significantly changed the manufacturing sector. This study investigates the complex effects of numerous AI elements on manufacturing industry labor forces. Concerns and opportunities surrounding AI's effects on employment, skill demand, job roles, and overall labor dynamics have surfaced as a result of the technology's rapid growth. It is investigated how AI may affect job security, employee engagement, and job happiness. In addition to initiatives to upskill and reskill workers, the report notes difficulties with workforce transfers and possible disruptions to established job hierarchies. A more flexible and responsive production environment is made possible by AI technologies, which also highlight prospects for human-AI collaboration.

Key words: AI impact on Labour forces

I. Introduction

A disruptive age for the industrial sector is just around the corner thanks to the quick adoption of Artificial Intelligence (AI) technologies in its essential operations. AI, which includes robotics, automation, machine learning, and data analytics, has the power to completely change how commodities are manufactured, optimized, and delivered. As this technological revolution progresses, it simultaneously raises concerns about its effects on the labor forces in the manufacturing sector and promises of enhanced productivity and efficiency. Manufacturing has always been a key component of economies, generating millions of jobs globally. From mechanization through industrialization to, more recently, digitalization, the sector's history has been characterized by waves of invention after waves of innovation. There is a great deal of discussion and research surrounding the possible effects of AI on manufacturing labor forces. As the conversation progresses, it becomes clear that the implications of AI on manufacturing labor forces are complex and dependent on a wide range of variables.

This study explores the complex interactions between labor forces and AI in the manufacturing sector. It intends to investigate the complex effects of AI technologies on employment, skill needs, job functions, workplace dynamics, and the overall socio-economic environment of manufacturing. Understanding these effects will help us negotiate the opportunities and difficulties that present themselves, allowing stakeholders to make wise choices about workforce planning in the face of an AI-driven future.

II. Review of Literature

Giri, S.(2020) outlined that AI adoption leads to the creation of new job roles and the transformation of existing jobs in manufacturing, requiring workers to upskill and develop digital competencies. As AI technologies are implemented, workers need to acquire skills to operate and collaborate with AI systems effectively, such as data analysis, programming, and human-machine interaction.

Mishra, A. K.(2020) stated that AI-driven automation in manufacturing may lead to job displacement, particularly affecting low-skilled and routine-based positions. Explanation: AI technologies can automate repetitive tasks, which may result in a reduction of certain job roles in manufacturing industries, requiring affected workers to seek new employment or acquire new skills.

Acemoglu, D., & Restrepo, P. (2019) found that increased automation through AI technologies in manufacturing can lead to job polarization, with growth in high-skilled and low-skilled jobs and a decline in middle-skilled jobs.

Yang, C., Xu, X., & Li, L. (2019) demonstrated that AI technologies, such as machine vision systems, can enhance quality control in manufacturing by detecting defects and anomalies more efficiently.

Feng, Y., Zhang, M., & Du, X.(2018) claimed that adoption of AI technologies in manufacturing can lead to improved operational efficiency, cost reduction, and enhanced product quality.

Chryssolouris, G., Mavrikios, D., & Papakostas, N.(2018) found that AI-based automation systems can enhance the flexibility of manufacturing operations, enabling rapid adaptation to changing customer demands and market dynamics.

Ceglarz, T., & Bello, O. D.(2018) found that AI can optimize production planning and scheduling processes, leading to reduced lead times, improved resource utilization, and increased production throughput in manufacturing.

Ramesh, R., & Cao, M.(2018) described that AI-based predictive analytics can enable proactive maintenance in manufacturing, reducing machine downtime, minimizing maintenance costs, and improving overall equipment effectiveness.

Cappelli, P. (2017) stated that implementation of AI in manufacturing can augment human capabilities, leading to increased productivity and efficiency.

Iansiti, M., & Lakhani, K. R. (2017) suggested that AI can enable the transformation of traditional manufacturing processes, leading to the development of smart factories and increased agility.

III. Objectives of the Study

The objective of the study is to know the impact of Artificial intelligence factors on labour forces in manufacturing industries.

IV. Research Methodology

Data Collection: The proposed study consists of both primary and secondary data. Secondary data will be collected through various books, journals and research reports. Primary data or the empirical data will be collected through well designed questionnaire in manufacturing industries of Andhra Pradesh State.

Research Design: The survey method was conducted using the simple random sampling method. 450 respondents are contacted for the analysis. Factor analysis and multiple regression tools were adopted for the analysis.

V. Research Findings

Table no.1.

Case Processing Summary			
		N	%
Cases	Valid	450	100.0
	Excluded[a]	0	.0
	Total	450	100.0
a. Listwise deletion based on all variables in the procedure.			

Table No.2

Reliability Statistics	
Cronbach's Alpha	N of Items
.772	33

Cronbach's alpha is 0.772 which is above than 0.7 that confirms acceptable reliability measure. From the above it assures to proceed for further analysis.

Table No.3

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.838
Bartlett's Test of Sphericity	Approx. Chi-Square	5129.471
	df	300
	Sig.	.000

Bartlett's test of Sphericity and the Kaiser-Meyer-Olkin measure of sampling adequacy is used. The Kaiser-Meyer-Olkin measure of sampling adequacy is .838 and the value of Bartlett's test of Sphericity is Significant. It indicates that the null hypothesis is rejected and these indexes prove that factor analysis for these variables is suitable and accepted.

Table No.4

Total Variance Explained									
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.375	25.500	25.500	6.375	25.500	25.500	2.985	11.938	11.938
2	2.858	11.434	36.934	2.858	11.434	36.934	2.953	11.813	23.751
3	2.220	8.879	45.812	2.220	8.879	45.812	2.766	11.065	34.816
4	1.456	5.823	51.635	1.456	5.823	51.635	2.603	10.413	45.229
5	1.277	5.109	56.744	1.277	5.109	56.744	2.137	8.547	53.776
6	1.134	4.535	61.279	1.134	4.535	61.279	1.876	7.503	61.279
7	.964	3.855	65.135						
8	.948	3.793	68.928						
9	.903	3.610	72.539						
10	.862	3.447	75.986						

11	.719	2.876	78.862						
12	.642	2.570	81.431						
13	.620	2.480	83.911						
14	.586	2.342	86.254						
15	.547	2.187	88.441						
16	.509	2.036	90.478						
17	.481	1.922	92.400						
18	.374	1.495	93.895						
19	.327	1.307	95.202						
20	.280	1.118	96.320						
21	.228	.912	97.232						
22	.212	.847	98.079						
23	.198	.793	98.873						
24	.163	.653	99.525						
25	.119	.475	100.000						
Extraction Method: Principal Component Analysis.									

Table No.5 Rotated Component Matrix

Rotated Component Matrix[a]						
	Component					
	1	2	3	4	5	6
B4	.860					
B3	.816					
B5	.773					
B2	.671					
B19		.875				
B18		.832				
B17		.776				
B20		.705				
B7			.868			
B9			.820			
B6			.818			
B8						
B26				.889		
B27				.885		
B28				.877		
B29						
B22					.733	
B21					.725	
B23					.649	
B24						
B25						
B13						.673

B12						.667
B14						.613
B11						
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.						
a. Rotation converged in 6 iterations.						

The artificial intelligence factors that influence labour forces working manufacturing industry were reduced from thirty-three to twenty and further grouped into six factors. Basing on the loadings in each factor, they were Job displacement, ethical considerations, skills upgrading, psychological & social impacts, skills mismatch and economic impact.

Table No.6 Variables Extracted to Groups

Variables Extracted	Group	Cronbach's Alpha	Action
B2,B3,B4,B5	Job Displacement (ID1)	0.866	Retained
B17,B18,B19,B20	Ethical Considerations (ID2)	0.856	Retained
B6,B7,B9	Skills Upgrading (ID3)	0.901	Retained
B26,B27,B28	Psychological & Social Impacts (ID4)	0.889	Retained
B21,B22,B23	Skills Mismatch (ID5)	0.705	Retained
B12,B13,B14	Economic Impact (ID6)	0.525	Removed

Table No.7 Variables Entered for Regression Analysis

Variables Entered/Removed[a]			
Model	Variables Entered	Variables Removed	Method
1	ID4, ID3, ID2, ID5, ID1[b]	.	Enter
a. Dependent Variable: DEP			
b. All requested variables entered.			

Table No.8 Regression Analysis-Model Summary

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.861[a]	.742	.739	.50376	1.510
a. Predictors: (Constant), ID4, ID3, ID2, ID5, ID1					
b. Dependent Variable: DEP					

The coefficient of determination, R square is the square of the sample correlation coefficient between outcomes and predicted values. It explains the extent to which changes in the dependent variable can be explained by the change in the independent variables. The independent variables that were studied explain only 73.9% of Overall satisfaction in commercial banks as represented by the R^2. Thus independent variables only contribute about 73.9%.The value Durbin Watson test is 1.510 which is above 1 and below to 2 which shows that there is no autocorrelation exists.

Table No.9 Multiple Regression Analysis

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.357	.145		-2.465	.014		
	ID1	.124	.028	.134	4.519	.000	.660	1.515
	ID2	.360	.027	.356	13.540	.000	.841	1.190
	ID3	.440	.025	.536	17.605	.000	.627	1.596
	ID4	.068	.024	.069	2.846	.005	.981	1.019
	ID5	.092	.028	.090	3.271	.001	.764	1.309
a. Dependent Variable: DEP								

Influence on Labour Forces =

-0.357 + 0.124 * Job Displacement + 0.360 * Ethical Considerations + 0.440 *Skill Upgrading + 0.068 * Psychological & social impacts + 0.092 * Skill Mismatch.

VI. Conclusion

All the coefficients reveal that they have a positive relationship with the influence on labour forces.

The p value of Job Displacement (ID1) is less than 0.05, and is positively influencing the labour forces in manufacturing industries.

The p value of Ethical considerations (ID2) is less than 0.05, and is positively influencing the labour forces in manufacturing industries.

The p value of Skills Upgrading (ID3) is less than 0.05, and is positively influencing the labour forces in manufacturing industries.

The p value of Psychological & social impacts (ID4) is less than 0.05, and is positively influencing the labour forces in manufacturing industries.

The p value of Skills mismatch (ID5) is less than 0.05, and is positively influencing the labour forces in manufacturing industries.

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