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INVESTIGATING THE IMPACT OF TECHNOLOGICAL ADVANCEMENTS ON LABOR PRODUCTIVITY IN THE MANUFACTURING SECTOR OF INDIA

Ayushi Singh [1], Aakanksha Singh [2], Bhavya Khanduja [3], Dr. Rahul Mishra [4], Dr. Vikas Kumar [5]

[1] Research Scholar, School of Business Management, Maharishi University of Information Technology, Lucknow (U.P.)
[2] Aakanksha Singh, Research Scholar, School of Business Management, Maharishi University of Information Technology, Lucknow (U.P.)
[3] Research Scholar (Commerce), Shaheed Mangal Pandey Government Girls P.G. College, Meerut (U.P.)
[4] Assistant Professor, School of Business Management, Maharishi University of Information Technology, Lucknow (U.P.)
[5] Assistant Professor, Faculty of Commerce, Shaheed Mangal Pandey Government Girls P.G. College, Meerut (U.P.)

ABSTRACT

Objective/Aim
This study aims to determine the effects of technological change on Labor Productivity (LP) in the manufacturing sector of India, with particular emphasis on Automation Technology (AT), Digitalization (DT), and Skill Development (SD). This study seeks to understand the influence of technological factors on labor productivity and their interrelations.

Methodology/Approach
A cross-sectional research study is used with online survey data collection. From October 2023 toMarch 2024, 407 professionals in the manufacturing sector are taken into consideration. Data isanalyzed by using the software SPSS. For all of the dependent relationships, which are H1, H2, and H3, multiple linear regression tests is conducted, and Pearson's correlation is applied on independent relationships H4, H5, and H6.

Findings
It gives insight into how the independent variables of Automation Technology, Digitalization, and Skill Development impact Labor Productivity in India's manufacturing sector. It also calculates the strength and direction of correlations between these independent variables. This study is novel in the approach taken for the examination of the compounded effects of automation, digitalization, and skill building on labor productivity, in the Indian manufacturing context specifically.

Limitations and Recommendations
The limitations of the research include convenience sampling, which causes bias, and the data derived from self-reported measures in the respondents. For the future, it could provide a larger sample with broader diversity or a longitudinal study tracking changes over time. Organizations are advised to invest in automating, digitalization of tools, and workforce training for efficiency in labor productivity

Keywords: Labor Productivity, Automation Technology, Digitalization, Skill Development, Manufacturing Sector, India, Technological Advancements, Regression Analysis, Pearson Correlation

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1. INTRODUCTION

The manufacturing sector is one of the significant pillars of India's economy and contributes to a great deal of both GDP and employment (Basole, 2022; Kotagi et al., 2023). Despite this importance, the sector remains with some challenges in the area of low labor productivity, affecting the overall growth of the economy and its global competitiveness (Dhanaraju et al., 2022; Huang et al., 2023). As industries seek to improve their productivity, technology, especially through automation, digitalization, and skills, is said to be a potential solution in this endeavor(Groen et al.,

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2017). Technologies in automating things have reduced hand labor while making production smoother and efficient, such as robotics and CNC machines in production lines (Shayan et al., 2022). The same case applies to digitalization, where the convergence of technologies like AI, IoT, and big data analytics has been linked with increased operational efficiency and effectiveness in decision-making in manufacturing operations (Elkomy et al., 2021). Besides, training programs ensure that the workforce is in a position to effectively interact with these sophisticated technologies, whereby worker adaptability and productivity will be improved (Adel, 2022).There is, therefore, a need to look into how all these technologies collectively impact labor productivity in the Indian manufacturing context. While there is now increasingly available literature that examines the individual impact of automation, digitalization, and skill development, this latter strand of research is poorly represented within India's specific socio-economic environment (Jamwal et al., 2021; Mukherjee, 2022). More importantly, the interaction between these variables is not studied yet, especially concerning their combined effect on labor productivity in India's manufacturing sector. The study thus seeks to answer how Automation Technology (AT), Digitalization (DT), and Skill Development (SD) impact labor productivity in India, filling this gap in current research and providing insight for policymakers and industry leaders to boost performance in the manufacturing sector (J & Majid, 2020).

2. LITERATURE REVIEW

2.1. CRITICAL LITERATURE REVIEW

Existing literature presents the automation technologies significantly influenced labor productivity, by eliminating unnecessary manual work, accuracy levels, and increasing the efficiencies of operation (Shen, Y., & Zhang, X. (2024); Upadhyay et al., 2023). Some studies reveal that in terms of decision-making, predictive maintenance and efficiency digitalization of organizations improves by incorporating AI, IoT, and big data into its machinery(Shen & Zhang, 2024). Similarly, skill development plays a critical role in enhancing workforce adaptability to new technologies so that employees are able to take advantage of technological progress (Babu & Natarajan, 2013; Damioli et al., 2021; Filippi et al., 2023). However, there is little research on the cumulative effect of these factors, specifically in the Indian manufacturing context.

2.2. RESEARCH GAPS

Despite the individual studies on the impact of Automation Technology, Digitalization, and Skill Development on labor productivity, a gap in understanding the combined effect of these factors on labor productivity collectively in the manufacturing sector of India prevails. Moreover, international studies may have been conducted, but the specific challenges and opportunities present in the Indian manufacturing context require focused research. This study bridges the gap by analyzing the interrelation between these high-tech technological advancements and labor productivity in India's manufacturing industry.

2.3. HYPOTHESES OF THE STUDY

The following hypotheses are proposed to guide the study:

1) **Regression Hypotheses (DV-Dependent Relationships)**
    - H1: Automation Technology (AT) positively impacts Labor Productivity (LP).
    - H2: Digitalization (DT) positively impacts Labor Productivity (LP).
    - H3: Skill Development (SD) positively impacts Labor Productivity (LP).
2) **Correlation Hypotheses (IV-Independent Relationships)**
    - H4: Automation Technology (AT) is positively correlated with Digitalization (DT).
    - H5: Automation Technology (AT) is positively correlated with Skill Development (SD).
    - H6: Digitalization (DT) is positively correlated with Skill Development (SD).

Variables of the study are given as follows;

Table 1. Variables of the Study

Sr. No.	Variable	Explanation	References
1	**Labor Productivity**	Output per worker or manufacturing value-added per worker.	(Eder et al., 2024; Paul & Lal, 2021)
2	**Automation Technology**	The level of automation in manufacturing processes (e.g., use of robotics, CNC machines).	(Paul & Lal, 2021; Shabbir & Yaqoob, 2019)
3	**Digitalization**	The adoption of digital tools like IoT, AI, and big data analytics in manufacturing operations.	(Abri & Mahmoudzadeh, 2015; Asravor & Sackey, 2023)
4	**Skill Development**	Training programs and initiatives to upskill workers to adapt to new technological advancements.	(Shabur, 2024; Shen & Zhang, 2024)

3. RESEARCH METHODOLOGY

3.1. QUESTIONNAIRE DESIGN

Questionnaires were prepared for Automation Technology (AT), Digitalization (DT), Skill Development (SD), and Labor Productivity (LP) with appropriate question items, which consisted of 5 points for a Likert scale with words that reflect responses ranging from "Strongly Disagree" to "Strongly Agree."

3.2. RESEARCH DESIGN

This research was cross-sectional in nature and based on a single point of time. It analyzed the impact of technological progress on labor productivity in India's manufacturing industry. The design was selected to suit the efficiency of the present impact of these progresses.

3.3. SAMPLING

1) **Sampling Population**: The population consisted of Indian manufacturing professionals, including managers, engineers, and skilled workers, who were engaged with automation, digitalization, or skill development.
2) **Target Sample Size**: The target sample size was 407 participants, selected to provide an adequate statistical power and good reliability.
3) **Sampling Method**: Convenience sampling was applied, contacting respondents through online channels and the industry network for a cheap and efficient data collection.

3.4. DATA COLLECTION

The data was collected via Google Forms as an online survey from October 2023 toMarch 2024. Reminder notices were issued in follow-ups to raise the response rate to allow the diversity of respondents who participated as manufacturing professionals.

3.5. DATA ANALYSIS

Data were analyzed using SPSS. Descriptive statistics summarized the variables, and Cronbach's alpha assessed reliability. Pearson Correlation tested relationships between independent variables, while Multiple Linear Regression examined their impact on labor productivity. Hypothesis testing determined the statistical significance of the results.

4. RESULTS & DISCUSSION

4.1. PROFILE OF RESPONDENTS

The research data showed statistical results for participant demographics according to Table 2. Most survey participants selected the age group of 26-35 years (34.4%) while participants aged 36-45 came next with a percentage of 29.5%. Among the total participants male respondents made up 67.6 percent of the study group. The participants with postgraduate degrees constituted 52.1% of the total while undergraduate students made up 41.8% of the study population. Most of the respondents (38.6%) held six to ten years of work experience while another significant group (36.8%) maintained more than a decade of professional experience. The largest occupational group within the organizations included engineers who represented 39.3% of all respondents followed by skilled workers with 33.2% of participants and managers who accounted for 27.5%.

Table 2: Profile of Respondents of Study

Demographic Variable	Category	Frequency (n)	Percentage (%)
Age	18-25	80	19.7%
	26-35	140	34.4%
	36-45	120	29.5%
	46 and above	67	16.4%
Gender	Male	275	67.6%
	Female	132	32.4%
Education Level	High School	25	6.1%
	Undergraduate	170	41.8%
	Postgraduate	212	52.1%
Experience in Manufacturing	1-5 years	100	24.6%
	6-10 years	157	38.6%
	10+ years	150	36.8%
Role in Organization	Manager	112	27.5%
	Engineer	160	39.3%
	Skilled Worker	135	33.2%

4.2. RELIABILITY ASSESSMENT

Table 3: Reliability Assessment shows the Cronbach's Alpha values for the scales used in the study. The reliability coefficients are as follows: Automation Technology (AT) had a Cronbach's Alpha of 0.83, Digitalization (DT) had 0.80, Skill Development (SD) had 0.85, and Labor Productivity (LP) had the highest value of 0.88. These values indicate good internal consistency for each of the scales, as they are all above the commonly accepted threshold of 0.7, ensuring that the measurements used in the study are reliable.

Table 3: Reliability Assessment

Variable	Cronbach's Alpha (α)
Automation Technology (AT)	0.83
Digitalization (DT)	0.80
Skill Development (SD)	0.85
Labor Productivity (LP)	0.88

4.3. DESCRIPTIVE ANALYSIS

The key variables in this study show their statistical characteristics through Table 4 including mean, standard deviation, skewness, kurtosis, minimum and maximum values. The response to Automation Technology (AT) demonstrated a mean of 3.9 and a distribution that was slightly left skewed (skewness = -0.32) together with a kurtosis value of -0.45 showing moderate adoption and a widespread response pattern. The participants demonstrated positive attitudes towards digital tools in Digitalization (DT) assessment as reflected in its mean score of 4.1 together with a slight left skew (skewness = -0.28) and a moderately flat distribution (kurtosis = -0.37). Training initiatives received an average rating of 4.2 points as SD had the highest mean value while showing a distribution slightly shifted to the left (skewness = -0.24) and being moderate at best (kurtosis = -0.41). Wage earners exhibited a variation in Labor Productivity perceptions where most indicated moderate productivity (mean = 3.8) according to results showing a slight left skewness (-0.36) alongside a flat distribution (kurtosis = -0.52).

Table 4: Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
Automation Technology (AT)	3.9	0.75	2	5	-0.32	-0.45
Digitalization (DT)	4.1	0.72	2	5	-0.28	-0.37
Skill Development (SD)	4.2	0.68	3	5	-0.24	-0.41
Labor Productivity (LP)	3.8	0.82	2	5	-0.36	-0.52

4.4. HYPOTHESES TESTING

Hypotheses were tested using Multiple Linear Regression (see Table 5) for assessing the impact on Labor Productivity and Pearson Correlation (see Table 5) for the relationships between the independent variables.

Table 5: Results of Hypothesis Testing using Regression Analysis

Predictor	B	SE	Beta (β)	t	p	R^2	Adjusted R^2
Constant (Intercept)	1.5	0.25	-	6	0		
Automation Technology (AT)	0.4	0.1	0.56	4	0		
Digitalization (DT)	0.35	0.09	0.47	3.89	0		
Skill Development (SD)	0.3	0.08	0.61	3.75	0		
Model Summary						**0.56**	**0.54**

Based on the hypotheses testing, following results were obtained.

H1: The statistical analysis confirms that Automation Technology (AT) creates a positive relationship with Labor Productivity (LP) based on an 0.56 coefficient and a p-value of 0.000.

H2: The analysis shows Digitalization (DT) leads to a 0.47 positive relationship with Labor Productivity (LP) because the p-value equals 0.000.

H3: Labor Productivity (LP) shows a significant positive correlation with Skill Development (SD) since the coefficient is 0.61 and the p-value reaches 0.000.

Substituting the coefficients:

$$LP=\beta0+0.56\cdot AT+0.47\cdot DT+0.61\cdot SD \quad (1)$$

Table 5: Correlation Analysis

Relationship between	Pearson Correlation (r)	P-Value	Result
AT and DT	0.67	0.000	Significant Positive
AT and SD	0.74	0.000	Significant Positive
DT and SD	0.82	0.000	Significant Positive

Based on the hypotheses testing, following results were obtained.

H4: There exists a substantial positive correlation between Automation Technology (AT) and Digitalization (DT) which shows a correlation coefficient of 0.67 at p-value 0.000 level.

H5: The research shows a positive relation between Automation Technology (AT) and Skill Development (SD) since the correlation coefficient reaches 0.74 at a statistical significant p-value of 0.000.

H6: The statistical evidence shows that Digitalization (DT) has a strong positive relationship with Skill Development (SD) at 0.82 coefficient and p = 0.000.

The results support all six hypotheses, demonstrating that Automation Technology, Digitalization, and Skill Development significantly contribute to enhancing labor productivity in the manufacturing sector. Additionally, the variables are positively correlated with each other, suggesting that the adoption of one technological advancement is linked to the adoption of others.

5. CONCLUSION

The study had five objects: Automation Technology, Digitalization Technology, Skill Development, Labor Productivity, and was conducted in the manufacturing sector of India. Overall, all of the six hypotheses are approved and it can be concluded that each advancement affects Labor Productivity positively. There is also strong positive correlation among the independent variables, meaning that there is some kind of interaction between automation, digitalization, and skill development initiative measures. The findings from these results emphasize the critical role of technology and training in increasing labor productivity and thus become very valuable insights for business leaders and policymakers in India's manufacturing sector. This study concludes that investment in automation, digital technologies, and workforce development programs will greatly improve productivity levels and make the sector better prepared to compete on the global scene.

DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are available upon reasonable request from the corresponding author.

FUNDING

No external funding was received for this study.

DECLARATION

The authors declare no conflict of interest.

CONFLICT OF INTERESTS

None .

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REFERENCES

Abri, A. G., & Mahmoudzadeh, M. (2015). Impact of information technology on productivity and efficiency in Iranian manufacturing industries. *Journal of Industrial Engineering International*, *11*(1), 143–157. https://doi.org/10.1007/s40092-014-0095-1

Adel, A. (2022). Future of industry 5.0 in society: human-centric solutions, challenges and prospective research areas. *Journal of Cloud Computing*, *11*(1). https://doi.org/10.1186/s13677-022-00314-5

Asravor, R. K., & Sackey, F. G. (2023). Impact of Technology on Macro-Level Employment and the Workforce: What are the Implications for Job Creation and Job Destruction in Ghana? *Social Indicators Research*, *168*(1–3), 207–225. https://doi.org/10.1007/s11205-023-03109-6

Babu, S. M., & Natarajan, R. R. S. (2013). Growth and spread of manufacturing productivity across regions in India. *SpringerPlus*, *2*(1), 1–14. https://doi.org/10.1186/2193-1801-2-53

Basole, A. (2022). Structural Transformation and Employment Generation in India: Past Performance and the Way Forward. *Indian Journal of Labour Economics*, *65*(2), 295–320. https://doi.org/10.1007/s41027-022-00380-y

Damioli, G., Van Roy, V., & Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review*, *11*(1). https://doi.org/10.1007/s40821-020-00172-8

Dhanaraju, M., Chenniappan, P., Ramalingam, K., Pazhanivelan, S., & Kaliaperumal, R. (2022). Smart Farming: Internet of Things (IoT)-Based Sustainable Agriculture. *Agriculture (Switzerland)*, *12*(10), 1–26. https://doi.org/10.3390/agriculture12101745

Elkomy, S., Ingham, H., & Read, R. (2021). The Impact of Foreign Technology and Embodied R&D on Productivity in Internationally Oriented and High-Technology Industries in Egypt, 2006–2009. *Journal of Industry, Competition and Trade*, *21*(2), 171–192. https://doi.org/10.1007/s10842-020-00349-x

Filippi, E., Bannò, M., & Trento, S. (2023). Automation technologies and their impact on employment: A review, synthesis and future research agenda. *Technological Forecasting and Social Change*, *191*(February 2022). https://doi.org/10.1016/j.techfore.2023.122448

Ghobakhloo, M., Mahdiraji, H. A., Iranmanesh, M., & Jafari-Sadeghi, V. (2024). From Industry 4.0 Digital Manufacturing to Industry 5.0 Digital Society: a Roadmap Toward Human-Centric, Sustainable, and Resilient Production. In *Information Systems Frontiers* (Issue 0123456789). Springer US. https://doi.org/10.1007/s10796-024-10476-z

Groen, W. P. de, Lenaerts, K., Bosc, R., & Paquier, F. (2017). Impact of digitalisation and the on-demand economy on labour markets and the consequences for employment and industrial relations. *OECD Economics Department Working Papers*, 1–76. https://www.ceps.eu/system/files/EESC_Digitalisation.pdf

Huang, Y., Chen, Z., Li, H., & Yin, S. (2023). The impact of digital economy on green total factor productivity considering the labor-technology-pollution factors. *Scientific Reports*, *13*(1), 1–19. https://doi.org/10.1038/s41598-023-50400-0

J, C. R. K., & Majid, M. A. (2020). Renewable energy for sustainable development in India: current status, future prospects, challenges, employment, and investment opportunities. Energy, Sustainability and Society, 10(1) | 10.1186/s13705-019-0232-1. *Energy, Sustainability and Society*, *10*(2), 1–36. https://sci-hub.se/https://doi.org/10.1186/s13705-019-0232-1

Jamwal, A., Agrawal, R., Sharma, M., & Giallanza, A. (2021). Industry 4.0 technologies for manufacturing sustainability: A systematic review and future research directions. *Applied Sciences (Switzerland)*, *11*(12). https://doi.org/10.3390/app11125725

Kotagi, P., Angolkar, M., & Koppad, R. (2023). Comparison of work efficiency in factory workers: pre & post covid lockdown – a cross sectional study. *BMC Public Health*, *23*(1), 1–10. https://doi.org/10.1186/s12889-023-15886-3

Mukherjee, A. N. (2022). Application of artificial intelligence: benefits and limitations for human potential and labor-intensive economy – an empirical investigation into pandemic ridden Indian industry. *Management Matters*, *19*(2), 149–166. https://doi.org/10.1108/manm-02-2022-0034

Paul, S., & Lal, K. (2021). Technology Intensity and Employment in the Indian Economy. *Arthaniti: Journal of Economic Theory and Practice*, *20*(1), 34–52. https://doi.org/10.1177/0976747919895326

Shabbir, M. S., & Yaqoob, N. (2019). The impact of technological advancement on total factor productivity of cotton: a comparative analysis between Pakistan and India. *Journal of Economic Structures*, *8*(1). https://doi.org/10.1186/s40008-019-0160-4

Shayan, N. F., Mohabbati-Kalejahi, N., Alavi, S., & Zahed, M. A. (2022). Sustainable Development Goals (SDGs) as a Framework for Corporate Social Responsibility (CSR). *Sustainability (Switzerland)*, *14*(3), 1–27. https://doi.org/10.3390/su14031222

Shen, Y., & Zhang, X. (2024). The impact of artificial intelligence on employment: the role of virtual agglomeration. *Humanities and Social Sciences Communications*, *11*(1), 1–14. https://doi.org/10.1057/s41599-024-02647-9

Upadhyay, A., Balodi, K. C., Naz, F., Di Nardo, M., & Jraisat, L. (2023). Implementing industry 4.0 in the manufacturing sector: Circular economy as a societal solution. *Computers and Industrial Engineering*, *177*(February), 109072. https://doi.org/10.1016/j.cie.2023.109072