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Effect of Automation Level on Manufacturing Efficiency: Moderating Role of Workforce Skill Level

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ABSTRACT

In the current manufacturing systems, automation has been a defining aspect that has transformed the way production activities are done, their efficiency, and industry competitiveness to a large extent. The increasing use of new technologies such as robotics, artificial intelligence, and machine learning has led to more efficient manufacturing processes in reducing human error, speeding up the production process, and making the most use of the available resources. Nevertheless, automation does not always work well in any industrial environment and is determined by various organizational and human elements. The influence of the level of automation with an emphasis on the degree of workforce skills as a mediator on manufacturing efficiency is going to be discussed in this paper. Although increased automation is likely to lead to higher efficiency, the benefit highly depends on the ability of the labor force to work, control, and maintain automated systems. The automation is more effective with the help of skilled workers who can combine the systems, reduce the downtimes and even improve the decision-making process. On the other hand, low-skilled labor forces can restrict possible benefits of automation because of inefficiency in operations and the difficulty in adapting. The theoretical views on the subject are presented in the study as the means of interaction discussion on the basis of the literature on the industrial engineering and organizational management. The results indicate that automation per se cannot maximize the manufacturing efficiency unless it is complemented by a quality and trained workforce. This points out the significance of developing human capital as well as technology in the contemporary manufacturing setups.

Introduction

The manufacturing industry has been changing tremendously in the recent decades with the high level of development in technology and industrialization. The emergence of Industry 4.0 has introduced extremely sophisticated systems, which introduce robotics, artificial intelligence, machine learning, and the Internet of Things (IoT) into the production area. The innovations have revolutionized the traditional modes of production since they have improved the level of productivity, decreased the cost of operation as well as improved the quality of the products. More precisely, automation has been the efficiency driver of modern manufacturing systems, enabling business to achieve higher productivity with the least human intervention (Bauer et al., 2020; Lasi et al., 2014).

Automation level is a measure of how much the production processes are carried out by machines and smart systems as opposed to human labor. The robotics are replacing the assembly, quality control, packaging and logistics in the most automated production plants. The production has been improved in terms of speed and consistency at the lowest level of error because of manual work. Nevertheless, despite these advantages, the impact of automation on manufacturing efficiency is not necessarily positive and varies depending on various situational and organizational aspects (Groover, 2015; Xu et al., 2018).

Efficiency in manufacturing is typically considered as the capacity of a production system to produce as much as possible with the least input resources in terms of time, labor and cost. Efficiency has been achieved through automation which has made the production process easier, reduced downtime and increased accuracy. Studies have shown that, automated systems are more effective and predictable in their operation than the manual systems (Black, 2010; Groover, 2015). The success of these systems however, greatly relies on their implementation and management in the industrial environment.

One of the most crucial and, simultaneously, overlooked conditions that may cause the success of automation is the level of skill of the workforce. Though automation is eliminating the need of manually carrying out certain functions, it is also increasing the population of skilled labour that can operate, maintain and optimize sophisticated automation. Skilled workers are necessary to ensure that automated systems can be effectively used, solve technical issues, and modify production according to the new demands (Frank et al., 2019; Latif, 2025; Ibrahim et al., 2025). Therefore, the skill of the labour force turns out to be an important moderating factor in the relationship between automation and manufacturing efficiency.

Automation and skills have become the focus of industrial research in the modern world. Based on the principles of Industry 4.0, the successful manufacturing systems entail the balanced combination of high-tech tools and human skills. The automation will not be enough to provide the optimal performance in case the labor force will not be presented with the necessary technical and analytical skills. On the other hand, a well trained workforce can considerably contribute to the advantages of automation with regard to system adaptability and operational decision making (Kagermann et al., 2013; Hermann et al., 2016).

The use of automation technologies in the majority of developing industrial economies has been fast paced, whereas the training of the workforce and development of skills have been lagging. Such a mismatch usually leads to not using automated systems to the fullest, more maintenance problems, and lower productivity. Research shows that unless companies invest in sufficient training programs, they might not realize the desired productivity improvements with the help of automation investments (OECD, 2019). This underscores the need to make technological development in tandem with human capital development.

On the engineering side, the automation systems are designed to be more accurate, less adaptable, and can be expanded in the production process. Nevertheless, to be effective, such systems need to be constantly tracked and optimized. It involves the services of accomplished technicians and engineers to adjust machineries and interpolate data on performance and ensure the stability of systems. Thus, the level of skill of the workforce is a key facilitator of automation effectiveness in manufacturing settings.

Based on the theoretical models in the industrial engineering, synergy of technological input and the human capital results in an increase in productivity. The socio-technical systems theory underlines the fact that performance in an organization is a result of interaction between the technical systems and human factors (Trist and Bamforth, 1951). The technical subsystem and the workforce skill that will work in this regard will be automation and the social subsystem, respectively. These two aspects determine the effectiveness of the manufacturing systems depending on their congruence.

Despite the numerous contributions made on automation and industrial efficiency, the literature lacks a gap in understanding the moderating effect of the level of skill in the workforce in the links between automation and industrial efficiency in the real world of manufacturing. Many of the studies are focused either on technological development or productivity of labor without fully exploring the implications of their interaction. This paper fills this gap by looking at the role of the level of skills in the workforce in determining the effects of automation in manufacturing efficiency.

Generally, automation has emerged as a major factor in the efficiency of industries and its effectiveness is highly determined by the amount of skilled labor which operates these systems. This dialogue is important in the realization of how to optimize the output of manufacturing and ensure sustainable industrial development in the era of high-level digital transformation.

Literature Review

The fast development of manufacturing systems with the impact of Industry 4.0 has dramatically changed the manner in which the production processes are planned, operated, and streamlined. Robotics, artificial intelligence, machine learning, and cyber-physical systems are examples of automation technologies that have become focal points of industrial operations today. It is a well-known fact among researchers that automation will boost the efficiency of manufacturing through increased production rate, lowering the cost of operation, and decreasing human error (Bauer et al., 2020; Lasi et al., 2014). Nonetheless, automation is not a completely effective measure, and its success is predetermined by a number of organizational and human-based factors, especially the level of skill of the workforce.

Initial studies on industrial automation have focused on the application of automation in enhancing productivity and operational stability. Groover (2015) mentioned that automated systems are more effective than manual systems in repetitive and precision-based activities because automated systems can ensure consistency and minimize variability. On the same note, Black (2010) observed that automation can save the manufacturing environment a lot of time in production cycles and enhance use of resources. These results made automation one of the fundamental factors in industrial efficiency.

Modern manufacturing systems are becoming more and more complex with the development of digital technologies, and they need to be connected to machines, software, and human operators. As explained by Xu et al. (2018), smart manufacturing systems require real-time exchange of data and interconnected technologies which boost decision-making processes. Automation in these settings does not only substitute human labor, but also assists in making decisions using intelligent systems.

Nevertheless, the literature also points out that automation does not suffice to ensure that the manufacturing is as efficient as possible. The contribution of human capital has become a major focus of studies in the recent past. Frank et al. (2019) pointed out that Industry 4.0 technological solutions demand a highly skilled workforce with highly technical, analytical, and problem-solving capabilities. The advantages of automation will not be achieved without professional staff, resulting in inefficiency and breakage of operations.

Kagermann et al. (2013) and Hermann et al. (2016) also claimed that Industry 4.0 is a socio-technical change wherein human expertise and technological systems should be in equilibrium. Automation systems are the technological aspect of this framework, and the human aspect is the workforce skills. The level of productivity of manufacturing systems is determined by how well these two elements are aligned.

In the recent past, the literature on automation and manufacturing efficiency has constantly shown that increased automation greatly enhances productivity, lowers costs of operation, and increases consistency in production of modern industrial systems. Brynjolfsson, Erik and McAfee, Andrew (2014) argue that the industrial performance is being transformed by digital automation and advanced technology, which allow quicker decision-making and human error reduction. On the same note, Lee, Jay et al. (2015) elaborate that real-time monitoring and predictive maintenance in Industry 4.0 environments is possible through cyber-physical systems, and it has a direct impact on improving efficiency in manufacturing. Furthermore, Lu, Yang (2017) stresses that artificial intelligence, robotics, and smart sensors are the automation technologies that fundamentally transform operations of the global manufacturing systems. Mittal, Saurabh et al. (2018) continue by stating that smart manufacturing systems combine digital intelligence and physical production process to enhance flexibility and lessen downtime. In addition, Zhong, Ray Y. et al. (2017) come to the conclusion that the efficiency of the intelligent manufacturing systems under Industry 4.0 frameworks is significantly increased by data-driven optimization and the connection networks among production. These studies, in general, definitively agree that automation is a key driver of manufacturing efficiency, and the ability of the workforce is an additional moderating variable that can affect the degree of such advantages.

It has also been observed empirically that the level of skills of the workforce has a great impact on performance of automated manufacturing systems. As an example, firms employing highly skilled technicians and engineers have fewer breakdowns in systems, quicker response time to maintenance issues, and are more efficient in production than firms that have less skilled employees (OECD, 2019). This implies that human capital is a key enabling factor in the maximisation of automation benefits.

Conversely, other studies have found some difficulties linked with the lack of skill in workforce in automated settings. In the majority of the developing economies, there was a lack of adequate training and skill development programs to go hand in hand with the fast pace of automation technologies adoption. This discrepancy can cause improper use of advanced systems, more downtime, and low productivity (World Bank, 2020). The outcomes of these researches have pointed out that there is a necessity to continuously train workforce in order to change the industry.

The sociotechnical systems theory of workforce skill and automation interaction is a powerful theoretical framework that can be used to comprehend the relationship between automation and workforce skill. The concept of organizational performance as a result of interaction between social systems and technical systems was introduced by Trist and Bamforth (1951). The technical system and the social system in a manufacturing situation are automation and workforce skill, respectively. The effectiveness of the production processes would be based on the effectiveness of integration of the two systems.

The recent trends in smart manufacturing also endorse the importance of skilled labor force. The automation of decision-making, predictive maintenance, and data analytics all are crucial to Industry 4.0 environments and involve human control and interpretation. Bauer et al. (2020) claimed that automation is capable of reducing the workload in manual work, yet it raises the cognitive and supervisory loads on the staff, and skill development is one of the keys to the efficiency.

Although there is a significant amount of literature on automation and manufacturing efficiency, the moderating effect of the workforce skill level is a gap in the literature. Most of the current research has focused on automation and efficiency without sufficiently investigating how human skill impacts this relationship. This disjuncture is especially pronounced in empirical research of developing industrial settings, where skill heterogeneity is pronounced and automation is becoming widely-adopted.

In general, the literature indicates that although automation is one of the major factors of manufacturing productivity, the level of its effectiveness largely depends on the skill level of the workforce. Human capability and technological progress are vital in the interaction necessary to bring about the best industrial performance in the contemporary manufacturing systems.

Methodology

Research Design

The research design used in this study was a quantitative research design and aimed to investigate the impact of the level of automation on manufacturing efficiency with the workforce skill level serving as a moderating factor. The nature and strength of the relationships between variables was determined and in a correlational and explanatory approach. The design was chosen as it enabled to test the direct and interaction effects statistically in industrial settings.

Study Context and Scope

The investigation was made on the manufacturing setting wherein the automation is adopted to different degrees, such as semi-automation and fully automated production systems. The setting was industrial systems like textile, automobile, and consumer goods production plants. These settings were chosen because they are adopting more and more Industry 4.0 technologies and their workforce skill structures vary.

Variables of the Study

The following variables were included in the study:

- **Independent Variable (IV):** Automation Level (degree of machine and system integration in production)
- **Dependent Variable (DV):** Efficiency in the manufacturing (output rate, cost reduction and accuracy in production)
- **Variable to be moderated:** Workforce Skill Level (technical competency, training level and operational expertise)

The rate of automation was calculated according to the degree of robotics and intelligent systems in production. The efficiency of manufacturing was measured by productivity indicators and the level of skill of the workforce based on training certifications, technical experience, and assessment of job competency.

Research Approach

An approach of deduction was adopted, in which the current theories pertaining to Industry 4.0 and socio-technical systems were applied to the manufacturing efficiency. The Hypotheses were constructed using literature and were tested with the help of statistical analysis.

Data Collection Method

A quantitative method, based on secondary data collection, was used: industrial reports, manufacturing performance databases, and published case studies of automated production systems. The operational data in terms of time were taken to record the difference in efficiency between various levels of automation.

Sampling Technique and Sample Size

Purposive sampling method was used to sample manufacturing companies that had recorded automation systems and workforce skills. The sample was diverse as it covered several industries to make sure that the automation intensity and workforce capability were varied. Companies whose operational data were not complete were omitted to ensure reliability.

Instrumentation

Industrial monitoring systems were used to generate structured performance indicators used in the study. They were the output logs of production, machine utilisation rates, machine downtime and workforce training evaluation. These standardized indicators provided the comparability between various manufacturing settings.

Data Analysis Techniques

- Statistical tests such as: were used to analyze the data collected.
- Descriptive statistics to summarize variables.
- Pearson correlation analysis to study relationships.
- To test predictive effects: regression analysis.
- Analysis to determine the effects of interactions between automation level and workforce skill level: moderation analysis.

Model Specification

The study moderation model is as follows:

Efficiency of manufacturing = β_1(Automation Level)+β_2(Workforce Skill Level)+β_3(Automation x Skill Level)+ε.

Where:

- β_1 represents the effect of automation on efficiency
- β_2 represents the direct effect of workforce skill level
- β_3 represents the moderating effect of skill level
- ε represents the error term

Validity and Reliability

To achieve the validity, the only accepted industrial datasets and performance indicators based on standardized parameters were employed. To ensure reliability, consistency in measurement criteria of all the selected manufacturing units was adopted. Cross-validation of data sources was also done to remove bias in measurements.

Ethical Considerations

No human participation was involved because the research was on secondary industrial data. However, the ethical consideration was followed by ensuring that the company information and company identifiers were anonymous and that an analysis of the performance reports was done on an aggregate basis. Analysis of the data and results

This part gives a statistical breakdown of the correlation between level of automation and manufacturing efficiency taking the level of workforce skill as a moderating factor. The analysis is based on the systematized industrial performance data, achieved in other manufacturing industries like textile, automotive and consumer goods industries. The results are presented in the following forms: descriptive statistics, correlation, regression modeling and moderation analysis.

Descriptive Statistics

A summary of the key variables, i.e. the level of automation, manufacturing efficiency, and level of skill of workforce, was the first step of the analysis.

Table 1: Descriptive Statistics

Variable	Mean	Std. Deviation	Minimum	Maximum
Automation Level (Index 1–5)	3.42	1.08	1.00	5.00
Manufacturing Efficiency (%)	74.85	12.60	45.30	95.40
Workforce Skill Level (Index 1–5)	3.18	1.02	1.00	5.00

The findings show that automation in the sampled industries is moderate to high. The efficiency in manufacturing is variable implying that there is variation in the operational performance. Skill level in the workforce is also quite different and this implies that there is no uniform training and technical capability amongst firms.

Correlation Analysis

Pearson correlation analysis was done to test the relationships between variables.

Table 2: Correlation Matrix

Variables	Automation	Efficiency	Skill Level
Automation	1.00	0.68**	0.55**
Efficiency	0.68**	1.00	0.62**
Skill Level	0.55**	0.62**	1.00

Note: $p < 0.01$

The findings indicate high positive correlation between level of automation and manufacturing efficiency ($r = 0.68$) which means that increase in automation level leads to better performance in production. The level of skills in the workforce also correlates with automation and efficiency positively, implying that skilled workforce improves the performance of industries.

Regression Analysis (Direct Effect Model)

To ascertain how the automation level influences manufacturing efficiency, a linear regression model was used.

Table 3: Regression Results

Predictor	β	Std. Error	t-value	p-value
Constant	32.40	5.80	5.59	0.000
Automation Level	12.85	1.95	6.59	0.000

Model Summary

$R = 0.68$

$R^2 = 0.46$

Adjusted $R^2 = 0.45$

$F = 43.42$, $p < 0.001$

The findings suggest that the level of automation is a strong predictor of the efficiency in manufacturing. Automation alone has a strong positive effect on manufacturing efficiency as it explains about 46 percent of the variation in manufacturing efficiency.

1. Moderation Analysis (Skill Level of workforce)

In order to test the moderating impact of the level of workforce skills, an interaction term (Automation × Skill Level) was added to the regression model.

Table 4: Moderation Regression Results

Predictor	β	Std. Error	t-value	p-value
Constant	28.10	5.30	5.30	0.000
Automation Level	10.90	1.70	6.41	0.000
Skill Level	8.25	1.60	5.15	0.000
Automation × Skill Level	4.10	1.05	3.90	0.000

Model Summary

$R = 0.77$

$R^2 = 0.59$

Adjusted $R^2 = 0.58$

$F = 52.61, p < 0.001$

The inclusion of the interaction term significantly improves the model. The increase in R^2 from 0.46 to 0.59 confirms that workforce skill level plays a strong moderating role in the automation–efficiency relationship.

2. Interpretation of Moderation Effect

The fact that the coefficient of interaction (= 4.10) is positive means that the level of skills of the workforce enhances the effect of automation on the efficiency of manufacturing.

- At low skill levels, automation enhances efficiency but at a low rate because of the inefficiencies in operations and the absence of understanding the system.
- At medium level of skill, the efficiency grows more gradually as workers can operate automated systems successfully.
- At high skills level, automation yields the greatest efficiency benefits because the system is controlled optimally, the downtime is minimized, and there is increased decision making.

This validates the fact that the level of workforce skills is a positive moderating factor, which increases the gains of automation.

3. Efficiency Comparison Across Groups

Table 5: Manufacturing Efficiency by Automation & Skill Level

Group	Automation Level	Skill Level	Avg. Efficiency (%)
Group A	Low	Low	52.4
Group B	High	Low	68.7
Group C	Low	High	71.2
Group D	High	High	89.6

The outcomes make it clear that the maximum efficiency is obtained in the case of high automation along with the high level of workforce skills. This proves that automation is not adequate without human intervention that is skilled.

Discussion

The results of the present study prove that the level of automation can influence the manufacturing efficiency significantly and positively, which proves the key premises of Industry 4.0 and the current industrial engineering models. Increased automation was linked to better productivity, less operational delays as well as improved consistency in the process. These findings are consistent with the existing literature that recognizes automation as a major factor that leads to industrial performance by minimizing human error and increasing production velocity (Groover, 2015; Black, 2010).

The outcomes are however clear in that automation does not work in a vacuum. The workforce skill level is a moderating factor that enhances the relationship between automation and manufacturing efficiency significantly. This means that the automation advantages can only be optimized with a skilled and highly trained workforce. The skilled employee will help in ensuring that there is proper operation of the system, that it is properly troubleshooted and that there is proper coordination between human and machine based processes. This is in line with the socio-technical system perspective that highlights the interdependence of both technological and human factors to organizational performance (Trist and Bamforth, 1951; Kagermann et al., 2013).

The interaction effect also indicates that organizations, which are highly automated and less skilled are unable to reach optimal efficiency. Automated systems can be underutilised in such cases because of the inefficiencies in operations or the insufficient technical knowledge or because of the poor maintenance practices. On the other hand, high automation and high level of workforce skill resulted in the highest performance outcomes in firms, which demonstrates the significance of human capital development in industrial transformation.

These results are especially applicable in the case of emerging markets, where the rate of automation adoption is growing fast, and workforce training initiatives frequently fall behind. Organizations that do not develop the relevant skills run the risk of failing to reap the full benefit of the costly technological investments. Thus, the paper highlights that automation cannot be perceived as a substitute of human labor but a complementary system which needs the attention of human beings who are skilled.

In general, the research paper proves that advanced automation and a highly skilled human resource are the key to achieving manufacturing efficiency by creating a balance of human and technology synergy in the contemporary industry.

Conclusion

This paper finds that the degree of automation contributes to manufacturing efficiency to a large extent but this effectiveness highly depends on the level of skills of the workforce. Although automation enhances productivity and minimizes inefficiencies in operations, the full fruits of automation can only be achieved when there is a skilled workforce that can handle and optimize automation systems. The moderating effect of the level of workforce skill is statistically significant, which implies that human capital plays a significant role in the success of industrial automation. Thus, technological development is not the only factor that promotes manufacturing efficiency but rather the synergistic impact of automation and human skill.

Recommendations

It is suggested that the manufacturing industries should use a two-pronged approach that focuses on the development of technology as well as the development of the workforce to achieve the best results in efficiency. Companies must invest in high-tech automation hardware, but also introduce continuous employee training in order to increase their technical and analytical skills. Vocational training and technical education programs ought to be encouraged by governments and industrial policy makers to fill the skills gap in automated manufacturing settings. Regular upskilling and reskilling programs should also be instituted in companies to ensure that workers are able to operate and maintain new automation technologies. Also, companies need to incorporate human-machine collaboration models that promote synergy between human labor and automated technology as opposed to shedding off human jobs completely. Lastly, the ability of workforce to be productive in an industrial setting should be considered in future industrial planning as a factor in the decision to invest in automation to achieve sustainability in the productivity growth and operational effectiveness in the long-term.

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