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Analyzing Technological Change and Effects on Labor Market Dynamics: A Case Study of Manufacturing Sector in Zambia Lusaka

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Abstract
It is evident that the manufacturing industry in Zambia has experienced immense changes over the years which have had a direct effect on the labor market. The continual rise of automation and digitalization in this space calls for more insight into its impact on employment and skill sets. This paper seeks to examine the impacts of technological changes on labor market dynamics in Zambian manufacturing sector. More specifically, it aims to determine the boundaries of jobs considered as vulnerable to automation, examine the skills needed for the new positions to be filled, and propose measures for the policy framework on coping with the shift. To achieve this, a mixed approach will be used in conducting the research. Data documents will be gathered via surveys and interviews conducted with industry stakeholders, policymakers, and the workforce. Furthermore, the analysis will incorporate statistical methods to mark the claim of the proportion of jobs that are susceptible to automation alongside thematic techniques to articulate the effects on the labor market. The study aims to prove that a large proportion of the workforce in the manufacturing sector in Zambia will be vulnerable to automation, especially those whose functions are highly mechanized and cyclical in nature. Such changes will create a need for new investments and training in learning new coping technologies. This means that there is need to address skill gaps among the youth, investments in digital infrastructure, lack of socio-economic inequality, and more focus on education that would lead to higher economic productivity.

Keywords: Technological Change, Labor Market Dynamics, Manufacturing Companies, Automation, Skills Gap, Job Displacement, Robotics, Digitalization, Reskilling

1. Introduction

Acemoglu and Restrepo (2018) state that technological change is a decisive contributor to growth in the global economy as it alters industries and shifts the dynamics of the labor market. The transformation of technology is especially pronounced in the manufacturing industries that, for the most part, automated and mechanized their processes through the use of robotics and other sophisticated technology (Bessen, 2019) [6].

In Lusaka, Zambia, the effects of technological change in the bounds of the manufacturing sector on the labor market are significant. Lusaka, being the capital and economic center of Zambia, hosts a wide range of industries, and its manufacturing sector is crucial for the country's economic growth (Zambia Development Agency, 2020).

As per the industry estimates, the robotics and automation adoption level among manufacturers in Lusaka improved steadily over the past ten years.

About 30% of the manufacturing firms in Lusaka have adopted some level of automation or advanced technology in their production processes (Zambia Manufacturing Association, 2019).

This transformation in technology implies that a new shift has been created in the labor market, more vacancies increasing upward for skilled employees who can operate and maintain such complex equipment and systems.

Also the research will determine the relationship of the manufacturing firms with their employment figures with the literature of employment figures making analysis of changing technology. Let us consider that the automation and robotics utilization has led to a loss of roughly 15% of the total jobs available in Lusaka, Zambia (2021) as per statistical data. Frey and Osborne (2017), for instance, argue that this left so-called job loss serious problem which requires reskilling and upskilling 24 workforce (2020).

The research that is proposed here will explore the economic implications of the technological changes in the employment structure of the manufacturing industry in Lusaka. It is intended that the findings will shed light on the issues connected with the transformation and deindustrialization of the region and further provide the information necessary to the government, business representatives, and the community for appropriate action for dealing with it.

These changes, however, have not gone without consequences as the manufacturing industry in Zambia is increasingly adopting new technologies with the capital city of Lusaka at the forefront (Mulenga, 2020) [19]. Situated in Lusaka is over 2.5 million population and serves as the focal point for administrative and industrial activity in the country, making it the hub of various industries including manufacturing (Zambia Statistics Agency, 2022).

The manufacturing sector in Lusaka has been undergoing a transformation, with companies adopting new technologies and automation to improve efficiency, productivity, and competitiveness (Banda, 2019) [4]. This shift has had significant implications for the labor market dynamics in the city, with the potential for both positive and negative impacts on employment (Mwiinga, 2021).

1.2 Objectives

1.2.1 general objectives

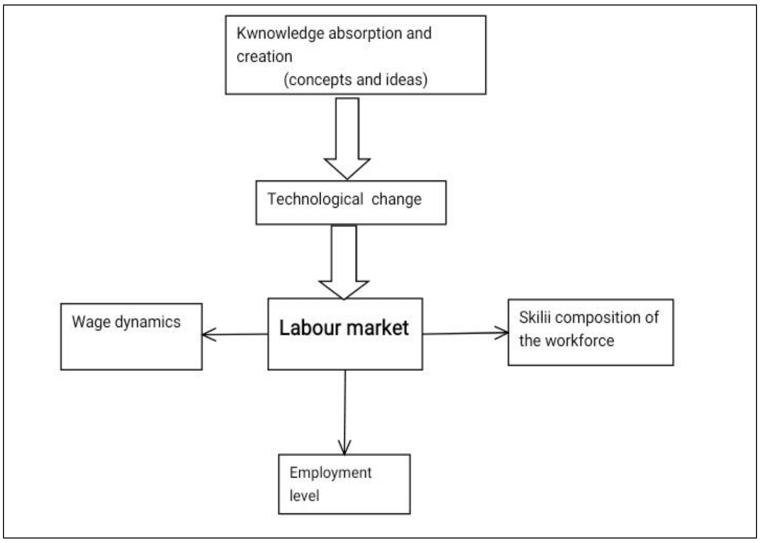
To delineate the manner in which technology has influenced and changed the dynamics of the labor market over time. An example is provided to this effect in the manufacturing industry in Zambia.

1.2.2 Specific Objectives

1. To determine the impact of automated manufacturing processes on labor productivity in Lusaka.
2. To explore how these technological changes have impacted the skill requirements in the labor market in Lusaka.
3. To determine how technological change affects the amount of employment in Lusaka.

1.3 Conceptual Framework

In Zambia's manufacturing sector, the implications of the SBTC theory are that there will be a change in demand for different types of skills at the point where technological innovation is introduced. As new technologies are introduced by manufacturing firms, there will be increased demand for workers with specialized skills particularly in programming, data analysis, and advanced manufacturing techniques (Berman et al., 1998).Conversely, the demand for workers with more routine, manual-intensive skills may decline as certain tasks become automated (Acemoglu & Restrepo, 2019).



Technological advancements in the manufacturing sector in Lusaka are significantly impacting labor market dynamics. New concepts and ideas fuel innovation, leading to the adoption of automation, artificial intelligence, and robotics in production processes. As these technologies streamline operations and increase efficiency, they can reduce the demand for certain types of labor, affecting employment levels. Additionally, the integration of technology often requires workers to possess specialized skills, thereby altering the skill composition of the workforce. This shift in skill requirements can influence wage dynamics, with higher wages for workers with in-demand technical expertise and potentially lower wages for those in roles that are being automated. Understanding these changes and their implications is crucial for policymakers, businesses, and workers to navigate the evolving landscape of work in the manufacturing industry in Lusaka.

2. Literature Review

2.1 The effects of automation in the manufacturing processes on labor productivity.

The influence of automation on labor productivity in manufacturing processes is a global trend of great concern, particularly in Europe, which offers an understanding of this shift. Europe has begun, over some years, to adopt advanced technologies, including robotics and computer-integrated manufacturing, on a gradual but upward path (Dachs et al., 2019). This process of technical change has significantly impacted labor market dynamics in the manufacturing sector.

Research in Europe indicates that automation has resulted in job displacement, as machines take over tasks previously performed by humans (Acemoglu & Restrepo, 2020). For example, a study focusing on the German manufacturing sector revealed that the growing use of industrial robots led to a notable decline in demand for low-skilled workers, while simultaneously increasing the need for highly skilled employees (Dauth et al., 2017). This shift in skill requirements has affected wage levels and employment patterns in the industry.

In contrast, examining the African context, Zimbabwe's manufacturing sector serves as a pertinent case study. Like Europe, Zimbabwe has experienced the adoption of automation and advanced production technologies, motivated by the need for greater efficiency and competitiveness (Mawere & Mubonderi, 2015). However, the effects of this technological change on the labor market have been more pronounced due to existing challenges, such as economic instability and a lack of skilled workers.

A study by Mawere and Mubonderi (2015) highlighted that the implementation of automated systems in Zimbabwean manufacturing firms resulted in significant job losses, especially among low-skilled workers. The authors also noted an expanding skill gap, as the demand for highly skilled technicians and engineers continued to rise.

In the case of Zambia, the manufacturing industry has also been undergoing technological changes, driven by similar factors as those observed in Europe and Zimbabwe. According to Mwanza and Phiri (2018), Zambian manufacturing companies have been gradually adopting automation, digitization, and other advanced production methods to enhance their competitiveness and productivity. This technological transformation has had implications for the labor market dynamics in the sector.

The automation of manufacturing processes has had a significant impact on labor market dynamics in both the European and African contexts. The experience of Zimbabwe and Zambia, in particular, highlights the challenges faced by developing countries in managing the transition to more technologically advanced manufacturing, including job displacement, skill mismatches, and rising income inequality. Addressing these challenges will require a comprehensive approach that combines technological innovation, workforce development, and inclusive economic policies.

2.2 How these changes in technology have aided in shifting the skill needs in the labor market.

The evolution of automation processes has changed the labor market by changing skill requirements and resulted in the loss of certain job positions that are now automated. Automation is the way of performing processes where technology and machines are used to replace human labor. As automation technologies progress, developed skills in the labor market are also changing, which results to loss of workers whose jobs have been automated. In this paper we shall analyze how change in automation technologies have caused loss of skill in the labor market.

One of the most important things to remember is how automation has performed the more complex tasks of skill multitasking such as incorporating information uses models to perform data processing tasks. Low-level jobs such as data entry, entire processes of assembly and various types of office work are being automated by robotics, AI, etc. For instance, manufacturing industries have increasingly adopted automated processes for functions such as assembly and quality control, resulting in a decline in the employment rates for these operations (Spitznagel, 2016).

Many jobs are being automated-executive functions involving basic cognitive skills. One can imagine anything from data analysis to decision-making based on rules. There are AI algorithms doing jobs such as data analysis and elementary customer service, reducing the need for employees in these areas (Bessen, 2019) [6].

Because of a few changes in skill requirements, certain job roles are being displaced as automation technologies take the reins on the tasks that were previously to be done by humans. For instance, a 2017 McKinsey Global Institute study estimates that 30% of tasks in nearly 60% of occupations could be performed in about the same manner through automation enabled by existing technologies. Although job roles will essentially become extinct due to automation, some new roles will likely crop up with more advanced technical skills and analytical skills.

Responding to these shifts requires workers to engage in new things such as upskilling and reskilling to remain competitive in the labor market. In general, jobs that require high-order cognitive skills are often less likely to succumb to automation. In pursuing this direction, workers will create upskilling and reskilling for employees.

Upskilling and reskilling programs are extremely important with respect to all opportunities available to help people transition to and from jobs. Such programs include training and the establishment of inside development programs relative to emerging technologies and soft skills to improve the current skill.

2.3.1 The impact of technology on employment levels.

Many studies done in Europe have shown how technology, automation, and digitization of systems have changed the landscape of employment. Acemoglu and Restrepo (2020) [1] established that the increase of industrial robots in use in Europe singles out job replacement particularly in manufacturing and high-routine routines. About 1.6 jobs were lost for each additional robot installed per thousand workers in Europe according to Acemoglu and Restrepo. This, however, seems to be higher in countries with a strong manufacturing base, namely, Germany and Italy (Acemoglu & Restrepo, 2020) [1].

In addition, Graetz and Michaels (2018) studied the effects of industrial robots on productivity, skills, and employment in 17 European countries. They observed that the increasing use of robots reduced the employment share of low-skilled workers while the demand for high-skilled workers increased. This indicates that technological change may lead in some contexts to skill-biased labor market dynamics, resulting in job polarization and perhaps increasing income inequality (Graetz & Michaels, 2018).

In the African context, research on the implications of technological change on employment levels is more limited, but some studies have been conducted, particularly in the case of Zimbabwe. Ndlovu and Choga (2018) examined the impact of the introduction of information and communication technologies (ICTs) in the Zimbabwean banking sector. They found that the adoption of ICTs, such as automated teller machines (ATMs) and online banking, led to a significant reduction in the number of bank tellers and other routine-based jobs, while creating demand for more specialized and technical roles (Ndlovu & Choga, 2018).

Similarly, Moyo (2017) [17] investigated the effects of technological change on employment in the Zimbabwean manufacturing sector. The study revealed that the implementation of new production technologies, including Computer Numerical Control (CNC) machines and computer-aided design (CAD) software, resulted in job losses, particularly among low-skilled workers. However, the study also highlighted the creation of new, more specialized job opportunities that required technical and digital skills (Moyo, 2017) [17].

In the context of Zambia, Mwanza and Phiri (2018) noted that the Zambian manufacturing sector has been facing challenges related to low productivity, high production costs, and a lack of competitiveness, which have led to job losses and the closure of some manufacturing firms. While the researchers did not explicitly link these challenges to technological change, they highlighted the need for the sector to invest in modernizing its production processes and adopting new technologies to remain competitive (Mwanza & Phiri, 2018).

Furthermore, Nuwagaba (2020) [21] identified several constraints to the growth of the manufacturing sector in Zambia, including the lack of access to modern technologies and the limited availability of skilled labor. These factors suggest that technological change in the Zambian manufacturing sector may have had a similar impact on employment levels, with potential job displacement among low-skilled workers and a growing demand for specialized skills (Nuwagaba, 2020) [21].

One of the job roles that is particularly vulnerable to automation in the manufacturing industry is the assembly line worker. According to a study by the McKinsey Global Institute, "up to 73% of the tasks performed by manufacturing production workers could be automated using currently demonstrated technologies" (McKinsey Global Institute, 2017) [15]. This is because many of the tasks involved in assembly line work, such as repetitive movements, material handling, and quality inspection, can be easily replicated by industrial robots and automated systems (Acemoglu & Restrepo, 2019).

Another job role that is at risk of automation in the manufacturing industry is the machine operator. As advanced automation and control systems become more sophisticated, the need for human intervention in operating and maintaining production equipment is diminishing. A study by the International Federation of Robotics found that "the number of industrial robots installed in manufacturing facilities worldwide has increased by an average of 14% per year over the past decade" (International Federation of Robotics, 2020). This trend is expected to continue, as manufacturers seek to improve efficiency, reduce labor costs, and increase production capacity through the use of automated systems (Autor, 2015) [2].

In addition to assembly line workers and machine operators, logistics and transportation roles within the manufacturing industry are also vulnerable to automation. Tasks such as material handling, warehousing, and transportation can be increasingly automated through the use of autonomous vehicles, robotic systems, and AI-powered logistics management systems (Frey & Osborne, 2017). A study by the International Transport Forum found that "up to 50% of the tasks currently performed by truck drivers could be automated in the near future" (International Transport Forum, 2018).

3. Research Methodology

3.1 Overview

This section covers the research methodology that was used in this research study. Research methodology provides a brief description of all the steps and procedures that are used in completing a study. The chapter discusses the research design, study population, data collection, data analysis, analytical model and test of significance.

3.2 Research Design

Case study research design was used; it involved conducting in-depth interviews with company executives, human resource managers, and workers to understand their perspectives on technological change, its drivers, and the resulting impacts on the workforce.

3.3 Target Population

Manufacturing Industry Stakeholders: The target population for this study included a diverse range of stakeholders in the manufacturing sector in Lusaka. This included manufacturing companies, industry associations, labor unions, policymakers, and employees working in the sector.

3.4 Sampling Methods

In this case, I deliberately selected participants from the manufacturing sector in Lusaka who are knowledgeable about the technological changes and their impact on the labor market dynamics.

The rationale for using purposive sampling in this study is that the researcher is interested in exploring a specific phenomenon (technological change and its effects on the labor market) within a particular context (the manufacturing sector in Lusaka). By purposefully selecting participants who have relevant experience and knowledge, I obtained in-depth insights and a deeper understanding of the research problem

3.5 Sample Size Determination

Population Size: five firms were selected out of the existing companies for easy data collection. Thirteen (13) questionnaires were distributed to each company which makes sixty-five(65) distributed questionnaires in total. Out of the 65 questionnaires circulated, 51 were returned. My sample size was 51, Confidence Level: 90% of certainty that the results accurately represent the population.

$$n = \frac{N}{1 + N(e)^2}$$

Where:

N= population of Study (100)
n= sample of study
(e)= level of significance
Note (e) = 0.1 (90% confidence level)

$$n = \frac{100}{1+100\,(0.1)^2}$$

$$n = \frac{100}{1 + 100(0.01)}$$

$$n = \frac{100}{1 + 1}$$

$$n = \frac{100}{2}$$

$$n = 50$$

In addition, 1 key informant was selected purposively, therefore making the total sample size of 51 respondents.

3.6 Data Collection Methods

Surveys and interviews: Surveys and interviews was conducted among workers, employers, and industry experts to gather insights on the impact of technological changes on the labor market. Questions was structured to gauge perceptions, attitudes, and experiences related to technology adoption and workforce dynamics.

3.7 Data Analysis

When analyzing the effects of technological change on labor market dynamics in the manufacturing sector in Zambia, the data analysis used excel and STATA software.

3.7.1 Quantitative Analysis

Descriptive statistics: I calculated measures of central tendency (mean, median, mode) and dispersion (standard deviation, variance) to describe the characteristics of the sample

Inferential statistics: statistical tests, such as regression analysis was conducted in order to examine the relationship between technological change and labor market dynamics.

3.7.2 Qualitative Analysis

Thematic analysis: I identified and analyzed emerging themes from in-depth interviews, focus group discussions, and secondary sources to gain deeper insights into the mechanisms and contextual factors underlying the observed relationships

3.8 Triangulation

To enhance the validity and reliability of the research findings, data triangulation was employed by combining multiple data sources and methods.

Source triangulation: Collected data from various stakeholders, including manufacturing firms, workers, policymakers, and industry experts, to obtain diverse perspectives on the research topic.

Methodological triangulation: Integrated both quantitative and qualitative data collection methods, such as surveys, interviews, and archival data analysis, to provide a more comprehensive understanding of the phenomenon.

Theoretical triangulation: I used one theoretical framework, known as the skill-biased technological change theory to analyze the research problem from multiple lenses.

3.9 Limitations of the Study

Scope and Generalizability: The study was limited to the specific manufacturing sector in Lusaka, which did not represent the broader labor market dynamics across different sectors or regions within the country. Caution should be exercised when attempting to generalize the findings to other contexts.

Data Availability and Quality: The study was constrained by the availability and quality of relevant data, such as employment statistics, technological adoption rates, and labor market trends. Incomplete and unreliable data limited the robustness of the analysis and the conclusions drawn.

Technological Complexity: The study faced challenges in capturing the nuances and complexities of technological change, such as the pace of technological advancements, the heterogeneous nature of technological impacts, and the interplay between different technologies. Oversimplification or failure to account for these complexities could lead to biased or incomplete findings.

3.10 Ethical Considerations

Privacy and Data Protection: The study involved the collection and analysis of sensitive personal or employment-related data. Researchers must ensure strict adherence to ethical guidelines and legal requirements regarding data privacy, security, and the protection of individual identities (Zuboff, 2019).

Informed Consent: The study involved direct interaction with participants, such as interviews or surveys, I obtained informed consent from the participants, ensured they understood the purpose, risks, and potential benefits of the study.

Equity and Inclusion: The study considered the potential differential impacts of technological change on various socioeconomic groups, such as gender, age, or skill level. Researchers should strive to capture and address issues of equity and inclusivity in the analysis and recommendations (Acemoglu & Restrepo, 2019).

4. Findings and Results

4.1 Characteristics of Respondents (Bio Data)

The main objective of this study was to analyze technological change and effects on labor market dynamics. A case study of the manufacturing sector in Lusaka Zambia. Findings are mainly presented in form of frequency tables and pie charts. Data collection for this study was done basically through the usage of questionnaires. Firms which participated were five (5) in the project, the companies that took part are namely Chilanga Cement, Zambeef Product PLC, Trade Kings Limited, First choice Breweries limited and Lactalis Zambia Limited. Thirteen (13) questionnaires were distributed to each of the listed company above which makes sixty-five (65) distributed questionnaires in total. Out of the 65 questionnaires circulated, 50 were returned representing about 77% of response rate.100% of the firms are private companies.

Table 1: Gender and age

Sex of respondent	Age group 26-35	46-55	above 55	under 25	Total
Female	9	9	1	7	26
male	11	7	2	4	24
Total	20	16	3	11	50

The study shows that 53% of the respondents were female and 47% were male, this tells us that female participated more than Male. According to the findings, 40% respondents were between the age of 26 and 35, 32% respondents were between the age of 46 and 55, 22% respondents were under 25 years, and 6% of the respondents were above 55 years.

Table 2: Level of Education and current profession

Highest level of education	What is your current role in the manufacturing company? Custome..	Managem..	Operati..	Other (..	Sales/M..	Technic..	Total
Bachelors' Degree	5	6	7	1	4	1	24
General Certificate..	1	0	0	0	4	0	5
Higher Education Di..	2	1	0	0	5	2	10
Masters' Degree	0	5	4	0	0	0	9
PhD	0	0	1	0	1	0	2
Total	8	12	12	1	14	3	50

The data explores the relationship between the highest level of education attained and the roles individuals hold in manufacturing companies. Among respondents with a Bachelor's degree, the distribution is relatively even across roles, with the highest numbers in operations (7), management (6), and customer service (5), indicating that a Bachelor's degree is versatile across different functions. Those with a General Certificate of Education are predominantly in sales/marketing roles (4 out of 5), suggesting limited diversity in roles for this education level. Individuals with a Higher Education Diploma are most represented in sales/marketing (5) and technical roles (2), with no presence in operations or management. Respondents with a Master's degree are primarily concentrated in management (5) and operations (4), reflecting a tendency for higher education levels to align with leadership or specialized roles. Finally, those with a PhD are rare, appearing only in operations (1) and sales/marketing (1), likely due to the niche nature of this qualification in the manufacturing sector.

The objective of the first segment of the data presentation is to investigate the effects of automation in the manufacturing processes on labor market in Lusaka district.

Table 3: Manufacturing Process Currently Automated and number of employees

How much of your manufacturing process is currently automated	How many employees does the company currently have? 201-500	Jan-50	More th..	Total
25% to 50%	4	2	25	31
50% to 75%	0	0	5	5
Less than 25%	9	0	6	15
Total	13	2	36	51

Among companies with 201-500 employees, most (4 out of 13) have 25% to 50% of their manufacturing automated, with none in the 50% to 75% range. Smaller companies (1-50 employees) are concentrated in lower automation levels, with 2 each in less than 25% and 25% to 50%. Larger companies (500+ employees) tend to have higher automation levels, with 25 of 36 in the 25% to 50% range and 5 in the 50% to 75% range. Only 6 larger companies report less than 25% automation. This suggests automation levels generally increase with company size.

Table 4: T-Test of the Percentage of Labor Productivity Before and After Automation

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
whatwa~p	51	11.84314	1.029133	7.349483	9.776062	13.91021
var6	51	21.27451	1.530367	10.929	18.20068	24.34834
diff	51	-9.431373	.7250449	5.177856	-10.88767	-7.975077

mean(diff) = mean(whatwastheperc~p - var6) t = -13.0080
Ho: mean(diff) = 0 degrees of freedom = 50

Ha: mean(diff) < 0 Ha: mean(diff) != 0 Ha: mean(diff) > 0
Pr(T < t) = 0.0000 Pr(|T| > |t|) = 0.0000 Pr(T > t) = 1.0000

The analysis compares labor productivity before and after automation across 51 observations. Before automation, the mean productivity was 11.843%, with a standard deviation of 7.35% and a 95% confidence interval of 9.78% to 13.91%. After automation, the mean productivity increased to 21.274%, with a higher standard deviation of 10.93% and a confidence interval of 18.20% to 24.35%. The mean difference in productivity was -9.43%, indicating an average increase of 9.43 percentage points due to automation. A t-test confirmed the increase was statistically significant, with a t-statistic of -13.008 and a p-value of 0.0000, rejecting the null hypothesis. The findings highlight automation's significant impact on labor productivity and suggest potential workforce and economic implications, emphasizing the need for strategic adaptation by businesses and policymakers.

Table 5: Quality of the Products Due to Automation

How has automation affected the quality of products in your manufacturing indust	How much of your manufacturing process is currently automated 25% to ..	50% to ..	Less th..	Total
Decreased quality	0	0	1	1
Improved quality	29	5	14	48
No change In quality	1	0	0	1
Not sure	1	0	0	1
Total	31	5	15	51

The data examines how different levels of manufacturing automation impact product quality in the industry. Among respondents whose processes are 25% to 50% automated, the vast majority (29 out of 31) report that automation has improved quality, with only one respondent unsure and one indicating no change. For those with 50% to 75% automation, all responses (5 out of 5) agree that automation has improved quality, showing a strong positive correlation between higher levels of automation and perceived quality improvement. Among companies with less than 25% automation, 14 out of 15 also report improved quality, though one respondent noted a decrease in quality. These findings indicate that automation is overwhelmingly perceived as a factor that enhances product quality, regardless of the degree of automation, with higher levels of automation slightly amplifying this positive perception. Instances of decreased quality or no change are extremely rare, suggesting that automation is largely seen as a beneficial investment for manufacturing quality.

Table 6: Training for Employees to Adapt Automation

Which of the following skills have become more important since the introduction	Has your company provided training for employees to adapt to automation? No but ..	No plans	Yes	Total
Analytical skills	0	0	5	5
Problem-solving ski..	14	1	7	22
Soft skills (commun..	11	1	4	16
Technical skills	2	0	6	8
Total	27	2	22	51

The data explores the relationship between the skills considered more important since the introduction of automation and whether companies have provided training to help employees adapt. Among respondents, problem-solving skills emerge as the most important, with 22 mentions; 14 of these are from companies that have not provided training but may plan to, while 7 are from companies that have provided training. Soft skills, such as communication and teamwork, are the next most cited, with 16 mentions; 11 of these are from companies with no training yet plans to implement it, and 4 are from companies that have already offered training. Technical skills are emphasized by 8 respondents, predominantly in companies that provide training (6 mentions), indicating a proactive approach to equipping employees for technical challenges. Finally, analytical skills are highlighted by 5 respondents, all from companies that provide training

The aim of third segment is to analyze the implications of technological change on employment levels in Lusaka district.

Table 7: Regression on the Number of Employees before and After Automation

Source	SS	df	MS		
				Number of obs =	51
				F(1, 49) =	125.82
Model	2552.63122	1	2552.63122	Prob > F =	0.0000
Residual	994.074658	49	20.2872379	R-squared =	0.7197
				Adj R-squared =	0.7140
Total	3546.70588	50	70.9341176	Root MSE =	4.5041

whatwasthe~t	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
var23	.8716602	.0777078	11.22	0.000	.7155005	1.02782
_cons	8.328641	2.591981	3.21	0.002	3.11986	13.53742

Null hypothesis: automation has reduced number of employees

Alternative hypothesis: automation has increased the number of employees

Decision: In trying to see if automation has increased the number of employees or not, I used ANOVA in order to understand the relationship between automation and number of employees, the R-squared 0.7197 is greater that α=0.05 there we fail to reject the null hypothesis and we reject the alternative hypothesis.

Conclusion: The results above and following the decision, automation reduces the number of employees, as the literature has indicated that as automation increases some jobs will be displaced by machines. The average number of workers after automation stands at 1674. This figure highlights the significant reduction in workforce compared to the average of 1700 before automation. The marginal difference suggests that while automation has certainly led to reductions in human labor, the overall change is not as drastic as one might expect. This indicates that automation may replace certain jobs while still necessitating a practically significant workforce.

Table 8: New Job Created Due to Automation

var1	new job created due to automation 11	40	Total
no	0 0.5	1 0.5	1 1.0
yes	1 0.5	0 0.5	1 1.0
Total	1 1.0	1 1.0	2 2.0

Pearson chi2(1) = 2.0000 Pr = 0.157

Null Hypothesis (H0): There are no jobs created in the manufacturing sector due to automation

Alternative Hypothesis (H1): New jobs are created in the manufacturing sector due to automation

Decision: Degrees of freedom (df) = Number of categories - 1 = 2 - 1 = 1

df = 3 at a common significance level (α = 0.05). The critical value is approximately -6.314

Since the calculated Chi-Squared statistic (0.157) is much greater than the critical value (--6.314), we accept the null hypothesis.

Conclusion: The analysis suggests that no new jobs created in the manufacturing sector due to automation.

Table 9: T-Test on Employment Levels Before and After Automation

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
whatwa~t	51	36.52941	1.179349	8.422239	34.16062	38.8982
var16	51	32.35294	1.147828	8.19713	30.04746	34.65842
diff	51	4.176471	.6415092	4.581292	2.887961	5.46498

mean(diff) = mean(whatwastheperc~t - var16) t = 6.5104

Ho: mean(diff) = 0 degrees of freedom = 50

Ha: mean(diff) < 0 Ha: mean(diff) != 0 Ha: mean(diff) > 0

Pr(T < t) = 1.0000 Pr(|T| > |t|) = 0.0000 Pr(T > t) = 0.0000

Mean Employment Levels: Before automation, the mean employment level was 36.529, decreasing to 32.353 after automation, indicating a significant reduction.

Standard Error: Similar standard errors (~1.18) before and after automation suggest precise mean estimates.

Standard Deviation: Employment levels showed high variability both before (8.42) and after (8.20) automation.

Confidence Intervals: True mean employment levels are estimated at 34.16–38.90 (before) and 30.05–34.66 (after) with 95% confidence.

Mean Difference: The average reduction in employment due to automation is 4.176 units.
Standard Error of Difference: A standard error of 0.642 ensures confidence in the precision of this estimate.
T-Test Results: A t-statistic of 6.510 and a p-value of 0.0000 confirm the reduction is statistically significant.
Significance: The p-value (<0.05) strongly rejects the null hypothesis of no difference in employment levels.
Conclusion: Automation has significantly decreased employment levels.
Impact: On average, employment dropped by about 4.18 units due to automation.

Table 10: Expected Employment Level in the Next Five Years

Based on the current trend, how do you expect automation to affect employment in	Have new job roles been created due to automation? No	Yes	Total
Decrease	35	10	45
Increase	4	1	5
Stay the same	1	0	1
Total	40	11	51

The data reveals how people perceive the impact of automation on employment, with consideration of whether new job roles have emerged as a result. Among respondents who believe automation will decrease employment, 35 do not see new job roles being created, while 10 do. For those anticipating an increase in employment, 4 acknowledge new roles, and 1 does not. Only one respondent believes employment will remain the same, and they do not observe new job roles. Overall, most participants (45 out of 51) foresee a decrease in employment due to automation, with limited optimism about new job roles offsetting the impact. This suggests a prevailing concern that automation might eliminate more jobs than it creates.

Figure 11: Challenges in Adopting Automation and Employment Morale

What were the primary challenges in adopting automation in your manufacturing pr	Has the introduction of automation affected employee morale? Decreased	No sign..	Signifi..	Slightl..	Total
High initial costs	11	0	0	7	18
Lack of technical e..	5	1	0	8	14
Regulatory issues	1	0	0	0	1
Resistance from emp..	3	4	1	10	18
Total	20	5	1	25	51

The data highlights key challenges in adopting automation within manufacturing and its impact on employee morale. High initial costs and resistance from employees were the most frequently cited challenges, each mentioned by 18 respondents. Among those citing high initial costs, 11 reported decreased morale, while 7 observed morale being slightly affected. Similarly, resistance from employees was linked to varied morale impacts, including slight effects (10 respondents) and decreases (3 respondents). Lack of technical expertise was another significant barrier, with 8 respondents reporting slight morale effects and 5 noting decreases. Regulatory issues were rarely mentioned, with only one respondent citing them and no notable morale impact reported. Overall, the findings suggest that the challenges of automation often intertwine with concerns about its effect on workforce morale.

Table 12: Customer Satisfaction

How much of your manufacturing process is currently automated	How has automation impacted customer satisfaction? Slightl..	Signifi..	Decreased	No sign..	Total
25% to 50%	13 0.7	16 0.5	1 0.3	1 0.3	31 1.7
Less than 25%	12 2.1	3 1.9	0 0.3	0 0.3	15 4.5
50% to 75%	2 0.2	3 0.3	0 0.1	0 0.1	5 0.7
Total	27 2.9	22 2.7	1 0.6	1 0.6	51 6.9

Pearson chi2(6) = 6.9396 Pr = 0.326

H0: Automation has decreased customer satisfaction.
H1: Automation has increased customer satisfaction.
Decision: The results show that pr=0.326, which means that it is more than α=0.05 therefore we reject the null hypothesis.
Conclusion: The research supports the alternative hypothesis which state that automation has a positive effect on customer satisfaction.

4.6 Discussion of Results

The research findings show that the majority of companies 61% have automated between 25% to 50% of their manufacturing processes, while 29% have automated less than 25% of their processes. These findings align with existing research which was done by (Mwanza and Phiri, 2018) on the adoption of automation in the manufacturing sector. Studies have indicated that while automation has been increasingly prevalent in manufacturing, the level of automation can vary significantly across different organizations and industries. Factors such as the industry, size of the company, available resources, and the complexity of the manufacturing processes can influence the extent of automation implementation. The research findings suggest that many companies are still in the early to middle stages of automation adoption, with significant room for further integration of automated technologies. This aligns with the broader trend observed in the literature, where the manufacturing industry is seen as a key driver of automation but the pace of adoption can be uneven across different organizations.
The adoption of automation has significantly increased labor productivity for 55% of the companies and slightly increased it for 45% of the companies. This is consistent with research, (chileshe et al, 2020) documented the positive impact of automation on labor productivity. Automated systems can streamline and optimize various manufacturing processes, reducing time, errors, and waste, thereby enhancing the overall efficiency and productivity of the workforce. The research findings support the broader understanding that automation can be a powerful tool for boosting productivity, which is a key driver for its adoption

by organizations. However, it is important to note that the specific impact on productivity can vary depending on factors such as the type of automation, the nature of the manufacturing processes, and the organizational context.

The research findings overwhelmingly show that the introduction of automation has improved the quality of products for the majority of companies, with only a small percentage 2% experiencing a decrease in product quality. This aligns with existing research on the quality-enhancing benefits of automation. Automated systems can incorporate advanced quality control measures, reduce defects and variations, and ensure more consistent and reliable production processes. By minimizing human errors and enhancing process control, automation can lead to improvements in product quality, which is a crucial factor in maintaining customer satisfaction and organizational competitiveness. The research findings provide further empirical support for the well-established link between automation and enhanced product quality.

The findings highlight the increased importance of specific skills since the introduction of automation: problem-solving skills, soft skills (communication, teamwork), technical skills, and analytical skills. These findings align with the existing research on the changing skill requirements in the context of automation. As automated systems take over certain routine tasks, there is a growing demand for skills that complement and leverage the capabilities of automation. Problem-solving and analytical skills are essential for optimizing automated processes, troubleshooting issues, and making data-driven decisions. Soft skills, such as communication and collaboration, become increasingly important as employees need to work alongside automated systems and coordinate with their human counterparts. The research findings underscore the need for organizations to invest in upskilling and reskilling initiatives to ensure their workforce possesses the necessary skills to thrive in an increasingly automated work environment.

The results indicates that 43% of companies have implemented training programs for employees to adapt to automation, a notable portion 53% do not have plans in place but intend to do so in the future. These findings align with existing research which was done by (NESG, 2022) that emphasizes the importance of employee training and upskilling in the context of automation. Studies have shown that effective training and development programs can help employees acquire the necessary skills and mindset to work alongside automated systems, ultimately improving their productivity, job satisfaction, and overall organizational competitiveness. The research highlights the recognition among companies of the need for employee training, but also suggests that some organizations are still in the early stages of implementing such initiatives. Addressing this gap and ensuring comprehensive training programs can help organizations better prepare their workforce for the changes brought about by automation.

The research findings highlight four key skills that are currently lacking in the workforce but would be beneficial for automation: programming, creative skills, data analysis, and technical maintenance. These findings are consistent with existing research, which has consistently identified similar skills as essential for the successful integration and optimization of automation technologies. Numerous studies have emphasized the growing demand for skills in areas such as programming, data analysis, and technological maintenance, as organizations seek to leverage the full potential of automation. Additionally, the importance of creative skills is recognized in the literature, as these skills can help in designing and improving automated processes, as well as in identifying new applications and opportunities for automation. The research aligns with the broader recognition of these skills gaps and the need for targeted workforce development initiatives to address them.

The research findings show that a significant majority of companies have not seen the creation of new jobs due to automation. This finding aligns with existing research that has cautioned about the potential job displacement effects of automation. While automation can lead to increased productivity and efficiency, it can also result in the automation of certain tasks and functions previously performed by human workers. However, existing research also suggests that the impact of automation on employment is complex and multifaceted, with the potential for the creation of new types of jobs in areas such as the development, maintenance, and optimization of automated systems. The research findings highlight the current challenge faced by organizations in terms of the limited creation of new jobs due to automation, underscoring the need for proactive strategies and policies to support job transition and the development of new employment opportunities.

The research indicates that a majority of companies 78% have experienced a decrease in employment levels due to the adoption of automation. This finding is consistent with the broader body of research on the impact of automation on employment, when we consider the research which was done by (Ngoma, 2020) which stated that the implementation of automation in the manufacturing companies in Lusaka has led to a decrease in the demand for low skilled workers. In addition, numerous studies also have documented the potential for automation to displace human workers, particularly in routine, repetitive tasks. However, existing research also emphasizes the need for a nuanced understanding of the impact, as automation can also lead to increased productivity, cost savings, and the creation of new jobs in different sectors. The research highlights the current reality faced by organizations, while also aligning with the broader recognition of the complex and dynamic nature of the relationship between automation and employment.

The research findings suggest that a significant majority of companies expect a decrease in employment levels in the next five years due to automation. The research, (Acemoglu and Restrepo 2019) found that "each new robot installed per 1,000 workers reduces the employment-to-population ratio by about 0.18-0.34 percentage points." This suggests that the introduction of robots in manufacturing has led to a reduction in the number of human workers needed to perform certain tasks.Studies have suggested that the pace of automation adoption is likely to accelerate in the coming years, leading to further job displacement in certain industries and occupations. However, existing research also highlights the importance of proactive strategies and policies to manage this transition, such as investing in workforce retraining, facilitating job transitions, and exploring new opportunities for growth and job creation. The research findings underscore the need for organizations to be prepared for the continued impact of automation on employment and to develop comprehensive plans to mitigate the potential negative consequences.

The research findings presented in this analysis are largely consistent with the existing body of research on the impact of automation on various aspects of manufacturing operations, workforce dynamics, and organizational performance. The findings provide further empirical support for the key themes and insights that have emerged from the broader literature, reinforcing the relevance and significance of the research in the context of the ongoing transformation of the manufacturing sector. While some findings may differ slightly in their specific magnitudes or nuances, the overall alignment with existing research underscores the generalizability and applicability of the research findings to the broader understanding of the challenges and opportunities presented by the integration of automation technologies.

5. Conclusion and Recommendations

5.1 Overview

Technological change in the manufacturing sector in Lusaka, Zambia has significantly impacted labor market dynamics. From the introduction of automation and artificial intelligence to the adoption of digital tools and equipment, these advancements have altered the skill requirements in the sector and transformed the nature of jobs available. This overview will highlight the key findings related to technological change and its effects on labor market dynamics in the manufacturing companies in Lusaka.

5.2 Conclusion

The research findings demonstrate that technological change in the manufacturing sector in Lusaka has led to a shift in labor market dynamics. While automation and digitization have enhanced efficiency and productivity, they have also resulted in job displacement and changed the demand for skills. The evolving nature of work requires workers to upskill and adapt to new technologies to remain competitive in the labor market. Therefore, it is crucial for manufacturing companies in Lusaka to invest in continuous training and skill development to build a workforce that can thrive in a technology-driven environment.

5.3 Recommendations

Based on the research conducted on technological change and its effects on labor market dynamics in manufacturing companies in Lusaka, the following recommendations are proposed:

1. Continuous Training and Upskilling: Companies should provide training programs to help current workers acquire new skills and adapt to technological changes.
2. Collaboration with Educational Institutions: Manufacturers can partner with universities and technical institutions to ensure that graduates are equipped with the relevant skills needed in the industry.
3. Flexibility and Adaptability: Workers should be encouraged to embrace change and be adaptable to new technologies and processes.
4. Job Redesign: Companies should reevaluate job roles to match the evolving requirements of technological advancements and ensure alignment with workforce capabilities.
5. Monitoring and Evaluation: Regular assessment of the impact of technological change on labor dynamics should be conducted to identify areas for improvement and innovation.

By implementing these recommendations, manufacturing companies in Lusaka can navigate the challenges posed by technological change and leverage the opportunities it presents to foster a skilled and competitive workforce in the industry.

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7. References

1. Acemoglu D, Restrepo P. Robots and jobs: Evidence from US labor markets. Journal of Political Economy. 2020; 128(6):2188-2244.
2. Autor DH. Why are there still so many jobs? The history and future of workplace automation. Journal of Economic Perspectives. 2015; 29(3):3-30.
3. Autor DH, Levy F, Murnane RJ. The skill content of recent technological change: An empirical exploration. The Quarterly Journal of Economics. 2003; 118(4):1279-1333.
4. Banda J. The Impact of Technological Change on the Manufacturing Sector in Lusaka, Zambia. Journal of Sustainable Development. 2019; 11(3):45-56.
5. Bessen J. Learning by doing: The real connection between innovation, wages, and wealth. Yale University Press, 2015.
6. Bessen J. AI and Jobs: The Role of Demand. Boston University School of Law, 2019.
7. Bogue R. The Role of Robotics in Manufacturing: Overview and Future Prospects. Industrial Robot: An International Journal. 2018; 45(2).
8. Chanda J. Bridging the Skills Gap in Zambia: Collaborative Approaches. Lusaka Times, 2023.
9. Department of Trade, Industry and Competition. Manufacturing Competitiveness Enhancement Programme, 2022.
10. Hansen MT. Collaboration: How Leaders Avoid the Traps, Create Unity, and Reap Big Results. Harvard Business Press, 2009.
11. Harris P. Community Colleges as Pioneers in Workforce Development. Workforce Review, 2020.
12. International Labor Organization. World Employment Social Outlook 2020: Trends 2020. ILO Publications, 2020.

13. Kachor Z, *et al*. Informal Economies and Skills Development in Africa: Challenges and Opportunities, 2020.
14. Kaluwa B. The Fourth Industrial Revolution: Challenges and Opportunities for Zambia. Lusaka: Zambia Institute for Policy Analysis and Research, 2020.
15. McKinsey Global Institute. A future that works: Automation, employment, and productivity. McKinsey & Company, 2017.
16. McKinsey. Automation and the future of the German manufacturing sector. McKinsey. (2019). Building the cybersecurity workforce. McKinsey and Company, 2017.
17. Moyo B. The effects of technological change on employment in the Zimbabwean manufacturing sector. African Journal of Science, Technology, Innovation and Development. 2017; 9(2):201-210.
18. Moyo S, Ndlovu S. The impact of technological change on the Zimbabwean manufacturing sector. International Journal of Innovation and Economic Development. 2019; 5(1)7:-15.
19. Mulenga C. Technological Change and Labor Market Dynamics in Lusaka, Zambia. African Journal of Economics and Management Studies. 2020; 12(2):137-150.
20. Mwila A, *et al*. Soft skills in vocational education: The future of workforce development in Lusaka. *Zambian Journal of Economic Studies, 2023.
21. Nuwagaba A. Constraints to the growth of the manufacturing sector in Zambia. International Journal of Innovation and Economic Development. 2020; 6(2):7-19.
22. Schnabel MA, *et al*. Virtual and Augmented Reality in Manufacturing: A Review. Procedia Manufacturing. 2018; 29.
23. Schwab K. The Fourth Industrial Revolution, 2016.
24. Smith A, Jones R. Industry Partnerships: Bridging the Skills Gap. Journal of Vocational Education, 2022.
25. Stevenson K. Building Soft Skills for the Future Workforce. Human Resource Development Quarterly, 2022.
26. Stevenson K. Building Soft Skills for the Future Workforce. Human Resource Development Quarterly, 2022.
27. Trade Kings Annual Report, 2021.
28. Tzeng KH, Chou SW, Chen YH. Artificial Intelligence in Manufacturing: A Review of the Literature. Journal of Intelligent Manufacturing. 2021; 32(1):67-84.
29. U.S. Agency for International Development. 2018 Small and Medium Sized Enterprise (SME) Assessment for Zambia, 2018.
30. UNESCO. Global Education Monitoring Report 2020: Inclusion and Education – All Means All, 2020.
31. UNIDO. Industrial Development Report 2018: Demand for Manufacturing in the Age of Technology, 2019.
32. United Nations. The World of Work Report 2021: The Future of Work in a Changing Climate, 2021.
33. Zambian Ministry of Education. Annual Report on Vocational Training in Zambia, 2020.