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Impacts of Technology, 4IR and Innovation on Job Opportunities in the Manufacturing Sector: South Africa's Case

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Abstract: The 4IR and other technological improvements are significant in global socio-economic life. However, this improvement is not only with opportunities as it is associated with some disadvantages. The general belief postulates that the Industrial Revolution would impede individuals' job opportunities. This study assesses the impact of the industrial revolution, innovation and other economic variables on job opportunities. This objective was achieved by applying the Johansen test for Cointegration and other econometric approaches on time series data from 1990 to 2023. Findings revealed the presence of a long-run relationship among variables. The ICT, innovation, investment and education levels were found to have a significant and positive impact on manufacturing employment while labour force growth has an inverse relationship with employment. The study demonstrates the importance of a combination of innovation and technology in creating jobs and enhancing individuals' life. Therefore, considering the study findings, it is recommended that, to improve employment opportunities in the manufacturing sector, the government and the Department of High Education should revise the studies curriculum to produce skilled and desired employers. Additionally, to benefit from the 4IR, the South African government is required to improve technological infrastructure to increase the number of citizens using use ICT.

Keywords: 4IR; ICT; employment; innovation; jobs; South Africa

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1. Introduction

The global economy in the 21st century is marked by significant vitalities caused by various events that include the 2008 financial crises, the COVID-19 pandemic and technological winds. During this era technology dominance and, an increase in sustainable employment opportunities have become at the centre of research and policy discussions. A large part of recent research focused on the implication of digital transformation in the global economy and employment in a specific way (Kolade & Owesen, 2022). The topical technological epoch that includes the fourth industrial revolution (4IR) comprised of artificial intelligence (AI), big data, cyber-physical systems, the Industrial Internet of Things and smart production are perceived as dominant key drivers of novel knowledge in the economy. This technological improvement came as economic opportunities yet with some challenges that may include skills gap widening, high inequality and job loss. Consequently, societal and educational transformation is required as a coping mechanism to maximize the technology growth improvement in terms of job opportunities and social welfare (Dhaou & Manda, 2019).

Although the South African labour market is still facing economic challenges such as slashing economic growth, high inequality, poverty, unemployment and mismatch between labour demand and supply; implementation and application of the 4IR tools can assist in enhancing economic growth and job creation. For instance, the 4IR is capable of creating new online businesses and jobs and increasing productivity which enhances economic growth and job creation (Fox & Signé, 2021). Additionally, technological developments are a key factor enabling individuals' work cognizance and enabling remote work expansion (Mckinsey & Company, 2019). However, as highlighted above, a mismatch between required competence and available skills remains a great challenge in the South African labour market. With the advent of the fourth industrialization, the traditional methods of economic growth and development through human production or labour intensive appeared threatened as they lost their feasibility for the future (Cunningham, 2018). Some college and university graduates leave their schools without acquiring sufficient digital literacy. Consequently, scholars deposit that societies particularly individuals are not yet ready to embrace challenges and opportunities that come with technological advancement, as the latter destroys existing jobs while creating new ones incompatible with existing working skills (Schofield, 2018).

The rise of artificial intelligence together with information and communication technology (ICT) within the manufacturing sector initiated what is now known as "smart production" (Cioffi, 2020) however, jobs created in the latter process necessitate innovative skills. It is estimated that 65 per cent of the current yang generation will be employed in new jobs that do not exist yet. These jobs will require technological skills (Apple Fostering, 2021). In other words, some of the existing jobs are threatened as, in developed countries, robotics is performing various types of work which previously necessitated human capital. Thus, future employment requires specific education levels, training and skills (Balkaran, 2010).

Irrespective of the mentioned challenges, the 4IR and other industrial revolutions are irreversible. Several studies were conducted to analyse the effect of the Industrial Revolution on the economy in general and productivity (Humphreys, 2020; Yang, 2022; Zhang, et. al, 2022). Those conducted focusing on South Africa were interested in investigating how 4IR or ICT affect economic growth, productivity and employment but, to the best knowledge of the author, none of these studies assessed the impact of 4IR or ICT on manufacturing (Abri & Mahmoudzadeh, 2015; Lefophane & Kalaba, 2020; Kaxorova, 2022; Solomon & van Klyton, 2020). Additionally, in their study, Malatji and Mabeba (2022) argue that despite its importance to the economy and welfare, the time for 4IR is not yet for the South African private industries. Therefore, the enigma remains the identification of manufacturing employment behaviour towards the presence of the 4IR. Will the 4IR help to reduce the unemployment rate or rather worsen the situation? The answer to this question resides in this study's core objective which is to assess the effect of 4IR on employment in the South African context. Before empirical analysis, the next section provides an overview of the existing literature followed by the presentation and discussion of approaches employed in this study. After the discussion of the findings, the study concludes with a concise summary, the study implications and policy recommendations.

2. Literature Review

Industrial revolution remains a controversial topic in both economic and social fields. On one side, the Industrial Revolution was a better tool to improve the economy and increase social well-being, whilst on the other side, the Industrial Revolution was perceived as a challenge, especially concerning employment opportunities. For instance, Khan (2016) argues that within five years, between 2016 and 2020, a combination of demographic, socio-economic and Fourth Industrial Revolution could cause the annihilation of more than 5 million jobs. In contrast, Khan et. al. (2023) assert that the industrial revolution is the engine of productivity growth and job opportunities. Additionally, not only does industrialisation increase the availability of goods and services, but it also reduces the required effort for an individual's daily survival. These controversial ideas highlight the importance of more studies concerning the role of 4IR on employment. This section of the literature covers theoretical and empirical reviews related to the topic of the study.

2.1. Theoretical Framework

Generally, employment is linked with the production process, and the latter is perceived as a combination of input to produce output. In this regard, technological change may play a significant role in enhancing the capacity of other inputs such as labour and improving the final output (Bennion, 1943). Assessment of the relationship between technology changes, innovation and employment, is an important and contemporary subject of discussion among scholars, economists and policymakers (Calvino & Virgillito, 2019). The literature provides a variety of theories that explain factors influencing employment behaviours. Those theories include, among others, Classical, neo-classical and Keynesian employment theories, Schumpeterian view of production methods, Marxian and Ricardian perceptions of technology and employment/unemployment, innovation and compensation theory. In this study, a few of these theories are discussed.

2.1.1. A Brief on Classical, Neo-Classical Keynes Theories vs Technological Unemployment

Technological unemployment refers to a situation in which individuals are jobless owing to labour-saving and innovative production processes initiated by an organization to solve the issue of the high cost of production. Therefore, technological unemployment is a structural unemployment concomitant with industry restructuring (Cords & Prettner, 2022). Nonetheless, the factual explanation of technological unemployment has become a controversial topic among researchers and economists. On one side, technological unemployment is considered as a sprawling monster subverting the world economy, while on the other side is considered as the doomsayers' mirage as the introduction of more machines in the production system disturbs the traditional idea of work. Thus, to some individuals, the use of technology should be limited to alleviate its negative impacts on employment opportunities while others are prone to its enhancement as it improves the quality of humanity's life (Campa, 2017).

The classical and neo-classical argue that machinery and labour-saving devices play a significant role in improving both exports and economic growth. Enhancing and including technology in economic sectors would increase revenue and create new employment. In the view of Smith (1937) however, improving technology would lead more to production and less labour demand, and subsequently cause unemployment. Smith's idea of labour division or labour division as a result of technological changes was supported by Thomas Malthus. However, this author's idea of technological unemployment was rejected by Jean Baptist Say (1964) stating that using technology would cause price adjustment and increase demand for technological products resulting in labour demand. Say (1964) argument was supported by David Recardo (1951) arguing that technological change would not only hurt labour prices (wages) but increase employment opportunities.

Ricardian and Marxian employment theories emphasise the effect of technology and innovation on job opportunities or employment (Ricardo, 1817; Marx, 1961). These two economists argue that innovation and technological improvement lead to unemployment as labour is replaced by machines in the production process. However, Marx and Ricardo ignored the "principle of factor substitution" under which, at a given price, the combination of labour and capital generates a profitable economy. Technology and innovation improvement can cause short-run labour demand destruction owing to the mismatch between required labour skills and supplied labour (Calvino & Virgillito, 2018). Therefore, innovation and technological improvement play a significant role in creating long-term employment. Ignoring Ricardo and Marx's hypotheses on the link between technology and employment, the concept of technological unemployment was reintroduced again by John Maynard Keynes (1930) after the 1929 economic crisis where he considered technological unemployment as "a new disease". Nonetheless, Keynes also perceived technological and innovation harm towards labour as a temporal phenomenon. He believed that technology and innovation may reduce working hours keeping the income constant (Campa, 2017). Consequently, technological progress can benefit everyone in the long term.

2.1.2. Innovation and Compensation Theory

By its definition, innovation refers to a process that allows producers to increase their production output using less quantity of factors of production essentially labour (Piva & Vivarelli, 2017) and consequently reduce the number of existing employees. An increase in output level with low labour is possible if a technology factor is improved and combined with labour. In Marx's view, technology does not free individuals from work and improve their well-being, it rather creates labour-wage reduction and income loss for a group of workers, while increasing human exploitation for individuals who continue working (Marx, 1976). Therefore, the Karl Marx theory (1961) commonly known as "compensation theory" argued that the balance in social life, amid joblessness caused by technology, could be achieved only if displaced labour is compensated. Marx's hypothesis was supported yet modified by Jean Baptist Say (1964) arguing that the innovation process can destroy jobs in one industry and create jobs in other industries where new machines are produced. Accordingly, Steuart (1966) argues that innovation reduces the production cost and selling price and consequently increases demand for goods and services which in return creates demand for labour. Combining these arguments, it can be concluded that innovation and technological changes do not only destroy jobs but also create new jobs. The challenge or task remains to know the difference between job creation and job destroyed by innovation and technology improvement (Hötte, et. al, 2023).

The compensation theory does not focus only on the importance of innovation, technological changes and employment creation through price changes, it also highlights the role played by investment fluctuations. The profit made through production growth resulting from innovation and technology is invested and used for future production which, in return, creates more employment (Ricardo, 1951; Marshall, 1961; Stoneman, 1983). The link between compensation theory hypotheses and industrialisation, suggests that the success of letter leads to economic expansion which is the source of employment opportunities. The job loss during the technological improvement, according to Ricardo (1821), is mostly caused by the skills mismatch and job-worker location. Thus, according to the Ricardian theory, technological improvement can only create structural unemployment which is generally temporally. Nonetheless, it is difficult to assess the magnitude to which technology improvement and innovation create and destroy jobs as net job growth in a specific economy cannot be determined by a simple comparison between the aggregate of new jobs created and old jobs destroyed (Freeman, et. al, 1995). Briefly, the majority of classical and neo-classical economists, argue that technology growth replaces labour demand and thereafter creates unemployment. Technological changes are like a double-edged sword. On one side it can create direct jobs and indirect job opportunities, while on the other side, it destroys jobs and thereafter creates unemployment (Freeman, et. al, 1995; Hötte, et. al, 2023). Nonetheless, some economists confirm that the long-term effect of technological improvement, that is creating jobs, outstrips the short-term effect which is job destruction (Arsić, 2020; Chawla, et. al, 2022; Keynes, 1930; Khan, et. al, 2023; Ricardo, 1821; Wang, et. al, 2022).

2.2. An Overview of the Industrial Revolution

The 18th century, around 1780, marked a significant change in humanity's history and that was the introduction of industrialization. The first industrial revolution started in England and was driven by waterpower and steam engines (Postelnicu & Calea, 2019). The first industrial revolution enables improvement in manufacturing, food availability and labour-saving (World Economic Forum, 2016). Stimulated by labour shortage and poor production, the Second Industrial Revolution (2IR) commenced during the second half of the 19th century (Van Dam, 2017). This period was marked by the invention of new technologies that included internal combustion engines, chemical industries, alloys, electricity, electrical communication technologies (telegraph, telephone and radio), petroleum, and running water with indoor plumbing (Gordon, 2000; Mohajan, 2020). Despite inventions and innovations that resulted in massive production, the 2IR increased industrial debt and consequently, labour was highly exploited with long working hours, dangerous working conditions, and decline in the overall health of the workforce, high inequality and low wages (Kaplan & Casey, 1958; Mohajan, 2020). Consequently, the 2IR was replaced by the third industrial revolution (3IR) driven by technological advances in manufacturing, distribution and energy factors. The 3IR changed the way people work, produce and entertain (Smith, 2001). In other words, through digital manufacturing, the 3IR created an economy of production and production growth, reduction and flexibility of inputs through easy-to-use robots, 3D printing and job creation within developed countries (Markillie, 2012, Rivkin, 2011). According to Rivkin (2011), the 3IR was built on five major pillars: transformation of the building stock into green micro-power plants to collect renewable energies on-site; the shift to renewable energy; and the use of Internet technology to transform the power grid of every continent into an energy internet that acts just like the Internet; deployment of hydrogen and other storage technologies in every building and throughout the infrastructure to store intermittent energies and transition of the transport fleet to electric plug-in and fuel cell vehicles. The third industrial revolution was driven by technologies of the digital engine of the Internet, renewable energy and 3D printing. The 3IR prepared the ground for the "digital economy" grounded on reindustrialization built on automation and cybernetics (Vătămănescu, et. al, 2018) leading to the fourth industrial revolution. Although the 3IR contributed to job creation and economic growth, it created a significant gap between these two economic variables. Application of technology leads to higher economic growth than employment growth in all economic sectors (Mcafee & Brynjolfsson, 2011; Rotman, 2013).

The transformation experienced in the 3IR laid the ground for the fourth industrial revolution (4IR). The latter marked a new era of evolution of manufacturing and chain production processes driven by technological innovations that include artificial intelligence (AI), 3D printing, biotechnology, blockchain, big data and Virtual, cloud Cyber-Physical systems (CPS), internet of thing (IoT), mobile, robotics technology and smart sensor (Abdin, 2019; Kagermann, et. al., 2013; Park, 2018). Major changes that characterised the Industrial Revolution from the first to the fourth are displayed in Figure 1.

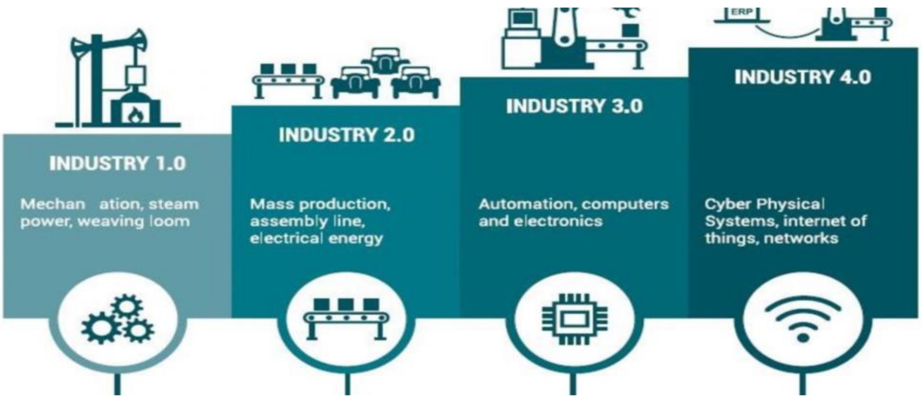

Figure 1. Industrial Transformations

The integration of integrating cyber-physical systems into the manufacturing production processes is one of the core objectives of the 4IR (Rojko, 2017). The production system introduced by the 4IR is expected to bring changes in nature of the human work and this creates great fear of employment sustainability (Postelnicu & Calea, 2019). The research conducted by the World Economic Forum with 15 major developed countries indicated that between 2015 and 2020 the global net employment was going to decline by more than 7.1 million jobs due to changes in job requirements. Nonetheless, Thompson (2015) argues that the 4IR technology will free individuals from unenjoyed work and enable them to perform smart and innovative activities. However, the reach of technological improvement benefits necessitates individual and societal transformation too.

2.2.1. Determinants of Key Drivers of the 4IR

After discussing the 4IR concept, it is significant to also discuss its determinants or key drivers of 4IR and industries' motivation to adopt the 4IR. The World Economic Forum (WEF) (2016) denotes that the capacity to prepare for and anticipate future job content, skills requirements and the cumulative effect on job opportunities is progressively important for individuals, businesses and governments to effusively grasp the chances convened by these changes and to alleviate adverse outcomes. In other words, the success of the 4IR will depend on the individuals, businesses and governments' ability and commitments to support of skills development, innovation and advanced technology (Saraswat & Verma, 2020). Key drivers capable of assisting in the adoption and implementation of the 4IR with societies include but are not limited to, education and training, Information, Communication and e technology, innovation and government policies.

2.2.1.1. Education and Training

The adoption of Artificial Interment (AI) in different sectors of the economy appears to be a challenge and an opportunity at the same time. The implementation of the Fourth Industrial Revolution is expected to create millions of novel jobs. However, these created new jobs require new abilities and skills from the labour force. In other words, as the new profession will be created by the 4IR, education and training for future jobs must shift the focus from old skills to new and technologically adapted skills (WEF, 2016). It is crucial to highlight that in the process of changing profession or job skills to accommodate new mechanism of working, the revolution creates a disruption in labour markets, and this may cause job loss for some employees whose stills are no longer in demand for new jobs (Saraswat & Verma, 2020). To overcome the issue of mismatch, there is a need to discern the 4IR required skills for trainers and institutions to develop those skills and integrate them with future systems.

2.2.1.2. Information, Communication and Technologies (ICT) infrastructure

Development in Information, Communication and Technologies play a pivotal role in easing access to information and accessing needed services without more difficulties (Murenzi & Olivier, 2017). Implementation of the 4IR technologies such as big data, cloud computing and the Internet of Things (IoT), in the workplace or in other fields of life is contingent on reliable and high-quality infrastructure to enhance effective integration between individuals, machines and systems. The example of those high-quality infrastructures is 5G wireless connectivity and broadband (Corfe, 2018).

2.2.1.3. Innovation

Innovation is another factor or driver of the fourth industrial revolution impacting employment in different economic sectors. In this regard, the word integration and market globalisation via phonological improvement required innovative enhancement in production approaches and business models to obtain a competitive advantage.

2.3. Review of Empirical Link between Technology and Employment

Various studies were conducted to assess the impact of technology in general and 4IR on labour demand or employment opportunities. This section highlights a few of those studies.

Analysing the impact of the impact of ICT and e-commerce on employment within European manufacturing, service industries, SMEs and large firms, Biagi and Falk (2017) found that neither ICT nor e-commerce had a negative impact on employment levels within the analysed industries. In other words, their findings opposed the hypothesis of the substitution between technological and employment growth. The Biagi and Falk (2017) findings were supported by other various studies including Abdurakhmanovna (2022), Benedicta and Lacheheb (2022), Osabohien (2023) and Younchawou and Moumie (2022) whose findings also corroborated the existence between technological growth and employment opportunities. Contrary, to these studies endorsing a positive relationship between technology and job opportunities, findings from Arsić (2020), Chawla, et. al. (2022) and Wang, et. al. (2022) revealed that ICT and technology in general may have an inverse relationship with employment.

Based on the findings presented in the above paragraph, technology can either destroy or create jobs. The mixture of Technological effects on employment opportunities was also established by some research. Tschang and Almirall (2021) investigated the implication of Artificial Intelligence (AI) on employment. The study found that the augmentation of AI creates employment distortions and consequently causes job loss in some economic sectors while creating jobs in others. Similarly, the study by Sharma and Aditya (2023) examined the impact of export diversification and ICT on aggregate and skill-level employment within 78 countries and found that the use of the internet promotes high-skill-intensive jobs and displaces low-skilled workers, while the use of mobile phones expands job opportunities for low-skilled workers.

3. Research Methodology

3.1. Data and Data Source

Through a quantitative approach, the study analyses the effect of 4IR on employment in South Africa. The empirical analysis of the impact of 4IR and innovation on manufacturing employed annual time-series data from 1980 to 2022. While the ICT components were used as a proxy for 4IR, the patent count was used as a proxy for innovation. Additionally, the study used two control variables namely gross capital formation and education level. The selection of these two variables was based on their impact on job creation. While the manufacturing employment data was acquired from Statistics South Africa (Stats SA), the rest of the variables were acquired from the World Bank's World Development Indicator (WDI) database.

Table 1. Variable's Presentation and Expectations

Variable	Variable description	Measurement	Expectation
MEMP	Manufacturing employment	Number of employed people /labour force*100	N/A
INOV	Innovation	Patent counts	positive
ICT/4IR			Positive/Negative
GFCF	Gross fixed capital formation	GFCF as a % of GDP	Positive
EDUL	Education level	High school pupils	Positive
LFOR	Labour force	% of total population ages 15-64	Negative

Source: Author's compilation

A priori, innovation, gross fixed capital formation and education level are expected to improve employment level in the manufacturing sector as they appear to be job creation drivers. An increase Labour force is expected to reduce the employment level as it increases the number of job seekers often incompatible with the required skills in the labour market. On the other hand, it is difficult to assume the effect of 4IR prior analysis as it creates jobs on one side while replacing or destroying jobs on the other side.

3.2. Model Specification

The effect of the 4IR and innovation on manufacturing employment in South Africa is implicitly expressed as follows:

$$MEMP = f(\text{INOV}, \text{ICT}, \text{GFCF}, \text{EDUL}, \text{LFOR}) \quad (1)$$

The above Equation 1 expresses manufacturing employment as an implicit faction of endogenous variables displayed in Table 1. The explicit form of the transformed variables is presented as follows:

$$lnMEMP_t = b_0 + (\ b_1 lnINOV_t +\ b_2 lnICT_t + b_3 lnGFCF_t +\ b_4 lnEDUL_t + b_5 lnLFOR_t + e_t \quad (2)$$

Where b_0 represents the intercept, b_0 to b_0 represents parameters to be estimated and e_t denotes the error term.

3.3. Estimation Approaches

The Johansen cointegration approach through the vector autoregressive (VAR) model and the impulse response function (IRF) technique are the two approaches followed to achieve the study objective. The Johansen test for cointegration is employed to determine the presence or absence of a long-run relationship between variables of interest. Consequently, through VAR (k) the cointegration equation is expressed as follows:

$$Y_t = \rho + \varphi_1 Y_{t-1} + \varphi_2 Y_{2-t} + \cdots + \varphi_k Y_{t-k} + v_t \quad (3)$$

Where Y_t is the vector of the endogenous variable; ρ represents the constant term; Y_{t-1} is the vector of the lagged endogenous; $\varphi_1\ to\ \varphi_k$ are the coefficient parameter matrices and v_t is the error term vector.

In a matrix form, Equation 3 is expressed as follows:

$$\begin{bmatrix} Y_t \\ Y_{t-1} \\ . \\ . \\ . \\ Y_{t-1} \end{bmatrix} = \rho + \begin{bmatrix} \varphi_1 & \varphi_2 & . & . & . & \varphi_k \\ 1 & 0 & . & . & . & 0 \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ 0 & 0 & . & . & . & 0 \end{bmatrix} . \begin{bmatrix} Y_{t-1} \\ Y_{t-2} \\ . \\ . \\ . \\ Y_{t-k} \end{bmatrix} + v_t \quad \text{...} (4)$$

Where Y_t denotes the vector of endogenous variables (MEMP, INOV, ICT, GFCF, EDUL, LFOR) stationary at the first difference I (1) and v_t denotes the vector of changes or shocks. As the aim of the study highlights, it is essential to determine the cointegration between the variables. Since all variables are stationary at the first difference, the Johansen approach is the adequate procedure to establish the long-run relationship. After performing the Johansen test for cointegration and determining the long-run relationship using Trace statistics and Max-Eigen statistics, the impulse response function (IRF) is performed to illustrate the reaction manufacturing employment to a shock from one standard deviation of explanatory variables. Another advantage of the IRF lies in its ability to evaluate the effectiveness and efficiency of a policy alteration on the target or response variable (Lin, 2006). A comprehensive impulse response function of Y_t at horizon h is expressed as:

$$IRF\ (h, \delta, I_{t-1}) = E[y_t + h|e_t = \delta, I_{t-1}] - E[y_t + h|I_{t-1}] \quad (5)$$

In Equation 5, δ denotes a one-time exogenous shock and the entire Equation 5 elucidates that the IRF represents the effect of the changes on the present and forthcoming values of the endogenous variable.

4. Results and Discussion

4.1. Correlation Analysis

Correlation analysis is one of the useful tools in determining a linear relationship between two or more variables. The correlation results presented in Table 2 suggest that except gross capital formation, all independent variables namely, innovation, technology components (ICT), education and labour force have a statistical correlation with employment in the manufacturing sector. Additionally, INOV, ICT and EDUL are positively correlated with employment while LFOR has a negative association with employment.

Table 2. Correlation Results

	MEMP	INOV	ICT	GCF	EDUL	LFOR
MEMP	1					
P-Value	-----					
INOV	0.75381	1				
P-Value	0.0000	-----				
ICT	0.50308	-0.89554	1			
P-Value	0.0028	0.0000	-----			
GCF	0.21639	0.08696	-0.15555	1		
P-Value	0.2265	0.6304	0.3873	-----		
EDUL	0.63583	-0.75508	0.50563	0.217874	1	
P-Value	0.0000	0.0000	0.0027	0.2232	-----	
LFOR	-0.71866	0.87597	-0.69619	-0.09813	-0.72050	1
P-Value	0.0000	0.0000	0.0000	0.5869	0.0000	-----

The unit root results from the ADF test conducted are displayed in Table 3. The ADF test was conducted considering the Akaike information criterion (AIC) lag selection.

The test also considered both intercepts and trends. However, the results indicated that none of the tested variables is stationary level, but they all become stationary after the first difference. Therefore, the Johansen test for cointegration is adequate to determine the long-run relationship among variables.

Table 3. ADF Unit Root Test

Variable	P-Value at level		Decision at level	P-Value at 1st Difference		Decision at 1st difference
MEMP	Intercept	Trends	Not stationary	Intercept	Trends	Stationary
INOV	0.1963	0.9931	Not stationary	0.0006	0.0002	Stationary
ICT/4IR	0.9998	0.8267	Not stationary	0.0102	0.0094	Stationary
GFCF	0.2645	0.5701	Not stationary	0.0005	0.0037	Stationary
EDUL	0.1965	0.9939	Not stationary	0.0007	0.0002	Stationary
LFOR	0.4144	0.3254	Not stationary	0.0000	0.0002	Stationary

4.2. Cointegration Test

As mentioned in the previous section, Johansen (1988) and Johansen and Juselius (1990) assisted in assessing the cointegration of the estimated variables. Table 4 displays both the Trace and Max-Eigen statistics obtained from the performed Johansen test for cointegration. The null hypothesis at none and most 1 are rejected at 0.05 significant levels as their P-values are 0.0000 and 0.0015 for the Trace test, and 0.0000 and 0.0004 for the Max-Eigen test respectively. In other words, Max-Eigen statistic and Trace statistics unanimously reject the null hypothesis of no cointegrating equation from two standpoints at 1% and confirm the presence of two cointegration equations amongst the variables. This implies that a long-run relationship exists between manufacturing employment, ICT, innovation and other variables included in the model.

Table 4. Cointegration Test

Hypothesised no. of CE(s)	**Trace**			**Max-Eigen**		
	statistic	**P-value**	**CV (5%)**	**statistic**	**CV (5%)**	**P-value**
None	156.3523	0.0000	95.75366	70.44993	40.07757	0.0000*
At most 1	85.90235	0.0015	69.81889	48.86789	33.87687	0.0004*
At most 2	37.03447	0.3459	47.85613	18.11632	27.58434	0.4855
At most 3	18.91815	0.4988	29.79707	12.95772	21.13162	0.4561
At most 4	5.960428	0.7002	15.49471	5.600027	14.26460	0.6649
At most 5	0.360400	0.5483	3.841466	0.360400	3.841466	0.5483

Note: * Denote rejection of the null hypothesis of cointegration

4.3. Vector Error Correction Model (VECM) and Cointegration Coefficients

After establishing the long-run relationship between variables, the study proceeds with the estimation of the long-run effect of independent variables on the response variable. Equation 6 below expresses the long-run coefficient in its implicit form. As indicated in the equation, all explanatory variables are statistically significant to influence the long-term behaviour of employment level within South Africa's manufacturing sector. While ICT, innovation, education and investment growth have a positive impact on job opportunities. Considering the extent to which each explanatory variable has on employment in the manufacturing sector, innovation and education level have a high positive impact on employment compared to other variables. In other words, a 1 percent increase in innovation and education resulted in approximately 26.31 percent and 6.734 increase in employment level respectively. On the other hand, the employment level increased by approximately 1.29 and 0.02 percent in response to a 1 percent increase in ICT and gross capital formation respectively. These results suggest that besides technology improvement, innovation and education are the major key drivers of employment opportunities in the manufacturing sector. However, though positive, domestic investment plays a small role in creating jobs in the manufacturing sector, this implies that foreign direct investment is dominating over domestic investment.

Contrary to these four explanation variables that passively influence job opportunities in the manufacturing sector, results in equation 6 infers that labour force increment negatively impacts employment in manufacturing. This implies that the majority of new labour force entrants lack the required employment skills in the manufacturing sector. In other words, there is a mismatch between labour demand skills and labour supply skills in the South African manufacturing sector.

MEMP = 1.690295 + 0.012921ICT + 0.263147INOV + 0.067379EDUL + 0.00022GFC – 0.0000629LFOR

[-1.42419] [-6.13703] [-713.390] [15.3355] [7.29208][1] (6)

4.4. Model Robustness and Diagnostic Test

Prior to the estimation of VECM and other econometric estimations, it is imperative to ascertain the status of the employed model. Therefore, various tests were performed to ensure the validity of the study findings and the robustness of the model. These tests include the Jaque-Bera test for normality, the Lagrange multiplier (LM) test for serial correlation and White for heteroscedasticity. The probability values of the three tests in Table 8 suggest the failure to reject the null hypothesis.

[1] [ ] denotes t-statistic.

In other words, the model residuals are normally distributed, free of serial correlation and homoscedastic.

Table 8. Residuals Diagnostic Test

Test performed	Probability value	Conclusion
Normality test	0.415	Residuals are normally distributed
Serial correlation LM test	0.529	Model Residual are free of correlation
Heteroscedasticity test	0.361	Model residuals are homoscedastic

4.5. VECM

The first importance of the Vector Error Correction (VECM) estimation is to determine the model's ability to revert to the long-run equilibrium after experiencing short-run shocks. Additionally, the VECM assist in establishing the short-run effect on independent variables on the response variable. Consequently, in this study, the VECM was performed to determine the short-run relationship amongst the cointegrated variables. As indicated in Table 9, the error correction terms (ECT) of D(MEMP), D(INOV) and D(ICT) are negative and statistically significant implying the model is eligible to revert to the long-run equilibrium after short-term shocks.

Table 9. VEM Results

Variable	**D(MEMP)**	**D(LFOR)**	**D(INOV)**	**D(ICT)**	**D(GCF)**	**D(EDUL)**
ECT-1	-0.016375	0.011724	−0.024273	−0.024273	−0.001801	−0.001801
Std. error	(0.00539)	(0.02172)	(0.00936)	(0.00936)	(0.00713)	(0.00713)
t-statistic	[-3.03999]	[0.53979]	[−2.5929]	[−2.59259]	[−0.2527]	[−0.2527]

4.6. Variance Decomposition Estimation

The estimation of the variance decomposition and impulse responses assisted in determining the causation relationship between explanatory and response variables. In the VAR system, the variance decomposition provides the percentage change of estimated endogenous produced by its counterpart endogenous variable. In other words, the variance decomposition explains the magnitudes of changes in each variable resulting from changes in another endogenous variable. The results in Table 10 display the power of explanatory variables (in ICT and Innovation) in deterring changes in manufacturing employment over 10 years. This period was divided into three categories where 1 period or one year denotes short-term, 5 years denotes medium term and 10 years and above denote a long-term. As indicated in the Table, short-term changes or shocks in employment rate are caused by manufacturing employment itself. However, as time goes by the employment self-influence declines while the power of other endogenous variables on employment changes increases. In the short term, 100 percent of employment shocks are explained by their changes and the latter explains around 60 percent and 57 percent in medium-term and long-term respectively. Innovation and education have a dominant power to cause changes in manufacturing behaviour. Irrespective of its growing power, ICT is the variable with the least power to cause shocks in South African manufacturing employment.

Table 10. Variance Decomposition of MEMP

Period	S.E.	MEMP	LFOR	INOV	ICT	GCF	EDUL
1	0.003959	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
5	0.010938	60.63267	2.599884	19.09563	1.598669	2.412515	13.66064
10	0.015519	57.80442	3.033532	20.31065	1.860239	2.269479	14.72168

4.7. Impulse Response Analysis

To assess the responsiveness or reaction of manufacturing employment towards shocks generated by exogenous factors, the researcher performed the impulse response analysis. The latter focused on responses of manufacturing employment towards innovation in the study's explanatory variables. Figure 1 displays the obtained results from the analysis.

The response of employment towards changes in education from the first year to the fifth is positive, between the 5th and the 6^{th} year is constant and from the 7^{th} year onwards it gradually declines. Contrary to its behaviour towards changes in education, manufacturing employment gradually decreases as a response to changes in gross capital investment. This implies that investment in the manufacturing sector is more technological improvement-orientated than labour production. The response of employment towards innovation in gross capital formation is supported by the response of employment towards innovation in the labour force. As the latter improves, yet with the investment in the sector focusing on technology production, employment responds by declining.

Based on these results from impulse response analysis, improvement in manufacturing employment is achievable only through solid education able to produce please with knowledge and skills necessitated by the industrial revolution and other innovative technology.

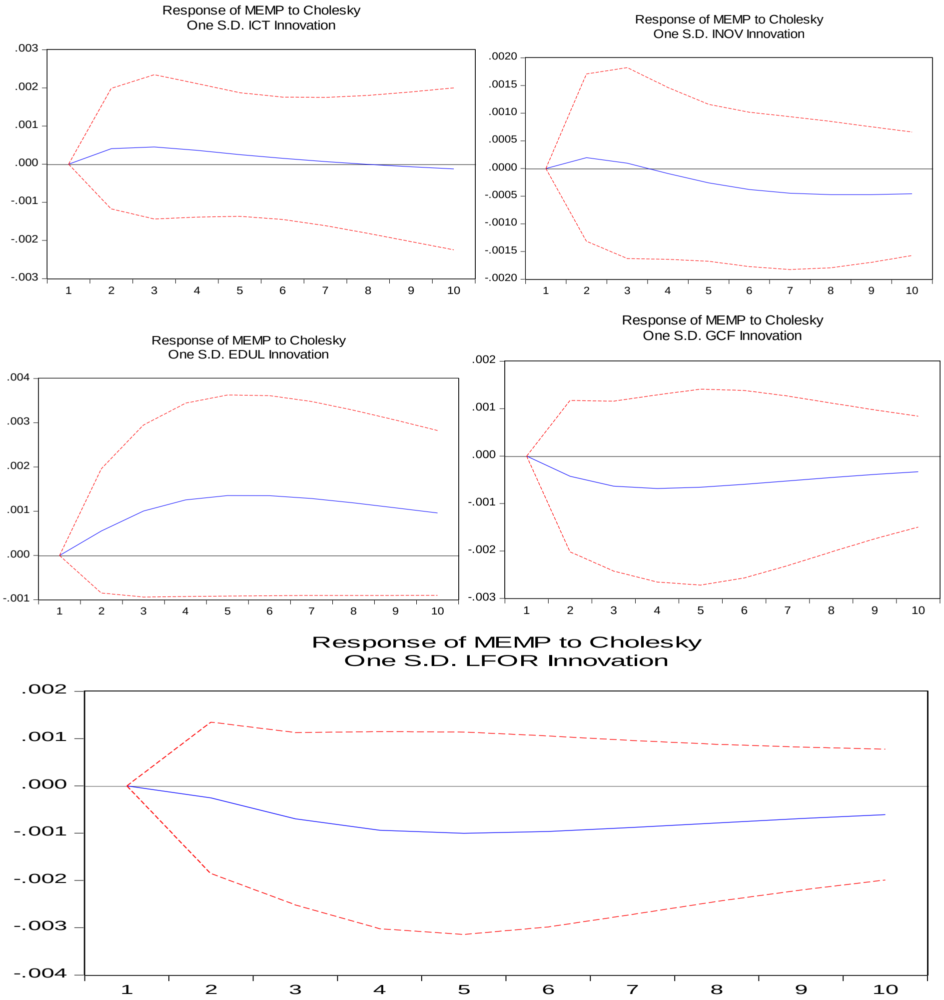

Figure 1. Response of Manufacturing Employment to Innovation in Explanatory Variables

5. Conclusion

The study aimed to analyse the long-run and short-run effects of the Fourth Industrial Revolution (4IR) and innovation on manufacturing job opportunities in South Africa. This objective was achieved using various econometric approaches such as the Augmented Dickey-Fuller (ADF) unit root test, Johansen test for cointegration, vector error correction model (ECM), variance decomposition and impulse responses.

The results from the ADF unit root suggested that all variables under consideration were stationary at first difference. Through the Johansen test for cointegration, the results from the Trace and Max-Eigen test statistic indicated the presence of at most two cointegrating equations. In other words, a long-run relationship exists between manufacturing employment, 4IR or ICT, innovation, gross capital investment, education level and labour force. The long-run results suggested that a positive relationship exists between ICT, innovation, education and gross capital formation. However, labour force growth was found to have an inverse relationship with manufacturing employment. Additionally, the variance composition outcome indicated that changes in education, innovation and investment influence employment behaviour more than ICT and labour force growth. Impulse response analysis, responds positively to changes in education and ICT while responding negatively towards changes in innovation, gross capital formation and labour force growth.

In consideration of the study findings, it is recommended that the South African government, specifically the Department of High Education, should improve its curriculum to produce skilled work desired in the labour market and reduce the mismatch between labour supply and labour demand. Additionally, for the success of 4IR on manufacturing employment growth, the government should improve technological infrastructure that includes schools' systems, communication networks and IT support. As ICT is a better tool for learning, connecting and diffusing necessary information about possible employment opportunities, South African policymakers should also enhance people's knowledge and access to technological tools.

Statements and Declarations

1. Funding acknowledgement

No funding was received for this study

2. Competing interests

The authors declare no potential conflict of interest.

3. Data Availability Statement

Data available on request from the authors.

Author Contributions

This article was produced by a solo researcher namely Dr Thomas Habanabakize. He is the one who conceptualized the topic, undertook the literature review, data collection, data analysis, results discussion and the rest parts of the manuscript.

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