The Impact of Technological Innovations on Employment in Manufacturing Sector: A Case of Pakistan Economy

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Abstract

This paper explores the impacts of technological advancement in the manufacturing sector in Pakistan's economy especially the information and communication technology (ICT) facilities. Using time series data and vector auto regression (VAR) analysis, this paper also analyses the dynamics of employment, technology and investment in a given time frame. Based on the importance of technological innovations, the study seeks to investigate the impact of technological innovations in Pakistan from 1995 to 2023.So, data from 1995-2023 was used to analyzed the model. The results reveal that the positive gains arising from ICT improvements are substantially unfavorable to employment and investment, primarily because of the adverse employment impacts from automation. Although the level of contribution by capital has been low in the achievement of employment and ICT is still the most dominant factor in growth. The result of the analysis is that the employment increases continuously even with the slowing down of both the ICT and investment which has long-term implication on the sector. In light of this, the current study offers a full perspective on how the enhancement of technology impacts on labor and capital procurement within the manufacturing sector of Pakistan. Study also reveals positive effects of ICT on employment were dependent on how skilled the workers were. And in the regions with low employment of that kind of skill, the advantages of more ICTs were limited and even led to downsizing of workforce rather than exploiting further utilization of workforce.

Keywords: ICT, Employment, Investment and VAR.

Introduction

Technological innovations are crucial for modern economies, with advanced countries like Japan, China, and South Korea investing billions in R&D and specialized divisions to transition from traditional to knowledge-based economies (Awan, at al, 2020). Pakistan is the fifth most populous country in the world with an estimated population of 253.8 million as of February 23, 2025, and has seen significant demographic changes, with a median age of 20.6 years, indicating a predominantly young population. In terms of employment, Pakistan's unemployment rate in 2023 was 5.5%, which was slightly lower than the previous year. The unemployment rate is the percentage of the labor force that is unemployed but available for and seeking employment. Both the unemployment rate and the labor force participation rate are important indicators of the country's economic health and employment dynamics (World Population Review, 2025; Worldometers, 2025).

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In 2024, Pakistan's manufacturing sector showed notable performance across various economic indicators like the industrial sector, encompassing manufacturing, mining, and construction, contributed approximately 18.2% share to Pakistan's GDP in 2023-24. In employment manufacturing sector employed about 14.9% of Pakistan's labor force while in exports, the manufactured goods accounted for approximately 71% of Pakistan's total exports These figures reflect the manufacturing sector's substantial impact on Pakistan's economic structure, employment and export activities in 2024 (Ministry of Finance, 2024). Being the lifeline in economic growth and employment, Industry productivity increases with technological advancements, with manufacturing sector claiming higher labor productivity than agriculture and services due to better utilization of fixed capital (Kreuser & Newman, 2018). Technology involves knowledge of skills and processes, and can be applied to machines without a comprehensive understanding of their mechanisms (Pohjola, 2000). Technological innovation refers to new or improved products or services that have characteristics significantly different from previous products and services (De Nooij, 2003). Technological advancements in manufacturing boost labor demand, reduce production costs, and increase marginal productivities, resulting in higher wages and returns to capital (Bessen, 2020). As recently, even low and middle-income economies have also contributed to international trade with investment in the innovation index (Tekin & Hancıoglu, 2019). Investment in research and development are important for developed and developing countries to expand their share in the global market by increasing exports (Azar & Drogendijk, 2018). Investment in research and development on the influence of technological innovation on manufacturing export is still scarce, more noticeably in Pakistan (Khan, 2023). Pakistan's manufacturing industry is crucial for GDP and employing and exporting products. Technological advancements can boost productivity but may cause labor displacement or skill needs. Pakistani manufacturers must focus on research, global practices, and continuous updates (Brynjolfsson & McAfee, 2014). Technology optimizes manufacturing, reducing production time and shortages, leading to increased productivity, economic growth, and job creation in new industries or fields (Aftab, 2019). Pakistan's low-income earners are vulnerable to automation's effects in labor-intensive industries like textiles, as robots replace traditional jobs. While some workers disappear, those managing these technologies grow. Technological innovation's contribution to Pakistan's economy remains inconclusive (Khan, 2020). Countries with educated and flexible labor force adapt better to technology adoption, creating new jobs. Pakistan's education system should focus on improving current education for future technology-driven economies (Goldin & Katz 2008). Pakistan is implementing vocational training and educational reforms to adapt to changing manufacturing sector mandates, despite existing gaps in technical education and technology education (Qureshi & Javed, 2019). Technological innovation could enhance Pakistan's local manufacturing sector, making it a part of global value chains. Advanced technologies can improve product quality, reduce costs, and meet international standards. Lifelong learning and professional development are crucial for Pakistan's competitiveness (UNIDO, 2021). Technological innovations in Pakistani manufacturing have boosted demand for skilled and unskilled labor, fostering economic growth and employment opportunities. Government policies, incentivizing research, creating a conducive environment, and reducing international market barriers, significantly influence this industry (Acemoglu & Restrepo, 2017). Technological innovation offers opportunities but also raises concerns about augmented inequality, as high-skilled workers often benefit from technological advancements, while low-skilled workers face job losses and earning-a-living gaps (Goldin & Katz, 2008). The government initiatives for research and development projects will enhance innovation, and high technology will become more accessible to small companies (UNIDO, 2021). Social policies, such as unemployment benefits, vocational skill retraining programs, and placement services, are crucial in addressing the negative impacts of job displacement caused by technological advancements (Qureshi & Javed, 2019). The extreme government support for innovation, coupled with the laid emphasis by research and development, constitute an essential role in the economy (Kim, 2018). On the contrary, Countries face challenges in transitioning to high-tech manufacturing, but community college and training initiatives offer hope by creating new job opportunities for displaced workers (Autor, 2019). Pakistan's manufacturing sectors are undergoing significant technological changes, necessitating effective transition management, clear communication about benefits and consequences, and employee involvement to mitigate resistance (Khan, 2020). Collaboration with stakeholders like government, businesses, and labor unions is crucial for adapting to new technologies, sharing knowledge, resources, and innovation opportunities, leading to increased employment (UNIDO, 2021).

Resultantly, technological innovation in the manufacturing sector of Pakistan possesses the capability of bringing about paradigm changes in the industry, elevating growth in the economy, and creating jobs. Though full of problems, all these benefits should be availed by all sections of the society. Some of the important means to attain the potential of technological progress include education and skill development, inclusive growth, and a friendly environment for innovation. These would increase global competitiveness, global value chains joining and therefore ensure the sustenance of the economic growth attained by Pakistan.

Objectives of the Study

- Analysis of relationship between employment, investment, and ICT.
- Investigation of influence of ICT on employment in manufacturing sector of Pakistan.
- To provide policy recommendations for ICT impact on employment.

Literature Review

The literature on the impacts of technological advancement on employment in the manufacturing sector in Pakistan’s economy especially the information and communication technology (ICT) facilities focuses on the efficient use of technological advancements. In this regard, it can the individual role of employment, ICT and investment.

Employment and ICT

Lee and Kim's (2018) observed that ICT application in semiconductors and automotive manufacturing by using a Dynamic Panel Data Model together with data from 2000 to 2016 and found that it led to increased high-tech job levels, creating jobs like research and development, software engineering, and system maintenance. However, the growth of high-skill jobs resulted in a decrease in low-skill employment, causing global job polarization in the manufacturing sector.

Ali and Javed's (2019) study examined the impact of ICT on manufacturing productivity. They conduct an empirical analysis utilizing data from 2014 to 2018 and an Ordinary Least Squares (OLS) regression model. They found that new ICT employment opportunities were created while low-skilled employment declined due to automation. The shift from low-skilled to high-skilled sectors in companies investing in ICT, particularly electronics and automotive, was evident.

Cirera et al. (2019) found that ICT adoption in the Brazilian manufacturing industry increased demand for skilled labor and reduced jobs for low-skilled workers. A Fixed Effects Model with data over 2000–2016 showed that automotive and electronics industries showed increased productivity and skill demand. However, the impact depends on regional industrialization.

Choi et al. (2020) studied the impact of ICT on employment in Sub Saharan Africa's manufacturing industries. They utilized a Generalized Method of Moments (GMM) model on panel data set covering a period of 2000-2015 and found that technology adoption positively impacted productivity, particularly in textiles and agro processing. However, the benefits depended on worker skill levels, with low-skilled regions potentially downsizing workforces rather than maximizing their potential.

Ahmed and Khan's 2020 employed Fixed Effects Model. They used the provincial data from the year 2005 up to the year 2019, found that industrially developed Punjab and Sindh provinces in Pakistan invested more in ICT than less developed ones, indicating that manufacturing sector development in these regions encourages ICT adoption for efficiency and competitiveness enhancement.

Rashid and Qureshi's (2021) investigated that manufacturing sector employment in Pakistan leads to higher digital skills generation among workers. They used survey data from 2012-2020 and a Logistic Regression Model to analyze the impact of ICT integration on workers' digital literacy and qualifications for complex machineries and software.

Malik and Iqbal's (2021) examined that workforce growth in medium businesses in the manufacturing industry increased the adoption of information and communication technology (ICT). By analyzing data from 2008 to 2018 using a Fixed Effects Model approach, they found that this increased use of ICT tools improved efficiency and market competitiveness, particularly in sectors like textiles, light engineering, and leather goods production.

Investment and Employment

Lee and Jung's (2017) explored by using VAR (vector autoregressive) model and data from 2000 to 2015 and found that employment growth in high-tech manufacturing industries, particularly semiconductors and electronics, led to increased investment in R&D and production infrastructure. This process, particularly in South Korea, influenced companies to invest in new technologies and expand production capabilities.

Khan and Raza's (2019) study examined the impact of employment on capital investment in Pakistan's manufacturing sector. They applied a time-series dataset from 1990 to 2018 and used an Autoregressive Distributed Lag (ARDL) model and found that increased employment, particularly skilled labor, was primarily due to modern machinery and production technologies. This increased confidence in production capacity and operational efficiency led to capital infusion into manufacturing projects.

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Ali and Qureshi's (2019) study found that increased employment in the manufacturing sector leads to increased investment in infrastructure like factories, warehouses, and transportation networks. Using OLS regression model with data from 2000 to 2018, they found that this increased investment attracts both domestic and international investors, indicating the industry's growth.

Ahmed and Shah (2020) studied the impact of regional employment growth on investment in Pakistan's manufacturing sector by using panel data from 2000 to 2017, they employed a Fixed Effects Model, particularly in urban industrial zones. They found that regions with higher employment growth, such as weekends and Sindh, attract sustainable investment due to the availability of skilled labor force, reducing production costs and increasing profits.

Butt, and Siddiqi, (2021) observed that Pakistan has been grappling with high inflation and a weakening currency, prompting the central bank to raise interest rates. While the intention is to curb inflation, high rates make borrowing more expensive. This discourages businesses from taking out loans for expansion or new ventures, limiting investment opportunities.

Feldstein's (2021) focused on US manufacturing employment. The author employed a Dynamic Panel Data Model with data ranging between 2000 and 2018. He revealed that growth in sectors like automotive, aerospace, and chemical manufacturing leads to increased capital stock of automation technology and spending on buildings. Manufacturers adopt new technologies when they anticipate a growing workforce and competitive pay, impacting investment decisions.

Methodology

This section describes the statistical approach used in research to examine the relationship between employment, investment, and information and communication technology (ICT) over time using statistical methods such as trend analysis, correlation analysis, and regression analysis using vector Auto regression (VAR) model.

Theoretical Framework

In a theoretical perspective, an inspirational Solow growth model curve had been adapted to comprehensively reviews and understands the evolution of technological innovation and employment in the manufacturing sector. Moreover, for the easy presentation of the outcomes and to avoid sharpness selected variables of the study, which is generally elaborated as;

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \mu \qquad \text{Eq (1)}$$

Eq. (1) represents the overall model current model where Y represents the dependent variable employment in symbolic form; while, '$\boldsymbol{\beta_0}$' is the models intercept which explores the relative change in employment when all the explanatory variables are zero. Study's slope coefficients of the possible explanatory variables are collectively expresses through the '$\boldsymbol{\beta_1}$' which represents the relative change in employment, either positive or negative due to unit change in $\boldsymbol{X_1}$ explanatory variables (ICT). Where as' $\boldsymbol{\beta_2}$' represents the relative change in employment, either positive or negative due to unit change in $\boldsymbol{X_2}$ control variable (investment). $\boldsymbol{\mu}$ represents the error term which captures the difference between the observed value and the value predicted.

Data Description (Stationarity Analysis)

Before time-series analysis, it's crucial to check if data are stationary, as non-stationarity can invalidate statistical inferences like hypothesis testing and forecasting due to spurious associations among variables, requiring careful analysis.

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)

The autocorrelation function (ACF) and partial autocorrelation function (PACF) are two critical techniques necessary to draw conclusions both on stationarity issues and the time series' temporal dependence structure.

Autocorrelation Function (ACF)
Auto Correlation Factor (ACF) measures correlation between time series observations, indicating autocorrelation. Slow ACF declines over time, making non-stationarity difficult to detect.

Partial Autocorrelation Function (PACF)
The PACF measure, which measures autocorrelation between time series observations, is crucial for determining the order of an autoregressive process, as a diverging PACF and convergent ACF indicate AR behavior.

Analyzing ACF and PACF for Stationarity
The ACF and PACF plots indicate that a stationary time series should have autocorrelation Functions and Parametric Autoregressive Coefficient Functions that decline sharply to zero over time.

Steps to Analyze ACF and PACF
Plot the ACF and PACF for Each Series
The ACF and PACF plots for employment, investment, and ICT are created through statistical software tools.

Interpret the Decay Patterns
If the slow decay or a pattern that does not converge to zero persists in the ACF, it indicates that the series is non-stationary. If it cuts off after just a few lags, it suggests an Autoregression of that order.

Transforming Data for Stationarity
Since all three variables are non-stationary, they need to be transformed to achieve stationarity before further analysis. Common transformations include:
Differencing: Taking the first or higher-order differences of the series to remove the trend component and achieve stationarity. The first difference of a series Y_t is calculated as;
$\Delta Y_t = Y_t - Y_{t-1}$

Trend Analysis
Trend analysis aims to examine changes in the variables over time to identify patterns or tendencies in employment, investment, and ICT. The following linear time trend model is used:
$Y_t = \alpha + \beta_t + \varepsilon_t$
Where: Y_t represents the value of the variable (employment, investment, or ICT) at time t, α is the intercept, β is the slope coefficient indicating the trend rate, ε_t is the error term. The trend analysis involves plotting the variables over time and fitting a linear trend line to detect increases or decreases over the years. The slope coefficient (β) indicates whether the trend is positive or negative.

Correlation Analysis
Statistical correlation analysis examines the magnitude and orientation of the linear associations among the variables, namely employment, investment, and ICT. The Correlation Analysis is calculated by the Pearson correlation coefficient (r).

Vector Autoregression (VAR) model

To find the relationship between ICT, employment and investment, a Vector Autoregression (VAR) model is employed. The VAR model captures the dynamic relationships among multiple time-series variables by considering the lags of each variable as predictors of all variables in the system. The general form of the VAR model can be expressed as:

$Y_t = A_1 Y_{\{t-1\}} + A_2 Y_{\{t-2\}} + ... + A_p Y_{\{t-p\}} + \varepsilon_t$

Where: Y_t is a vector of the endogenous variables (employment, investment, ICT), A_i are matrices of coefficients for lag i,P is the number of lags, ε_t is a vector of error terms.

Forecasting

The VAR model is also employed for forecasting future values of employment, investment, and ICT. Forecast intervals are calculated using the following formula:

$$\mathrm{CI} = \hat{Y}_t \pm Z_{\alpha/2} \cdot \mathrm{SE}(\hat{Y}_t)$$

Table 1: Summary of the variables taken under consideration

Symbols	Description	Sign	Source
Dependent Variable			
EMP	Number of employed after 15 year	------	**PSB, PES**
Independent Variable			
ICT	Information communication technology	-/+	**PSB, PES**
INV	Investment with annual percentage	+	**PSB, PES**

Analysis of Data

The data analysis shows the relationship between employment, investment, and ICT in the manufacturing sector using various statistical techniques. Based on the descriptive statistics, time series plots, regression analyses, and forecasts, several important findings emerge.

Descriptive Statistics

An examination of the descriptive statistics in Table 1 reveals the levels of variability of each variable. The employment feature has a mean of 49.73 with very low standard deviation (0.655). Investment displays a low coefficient of variation, with an actual mean and standard deviation of 1.002 and 0.703 respectively ICT on the other hand has a mean of 14.445 along with higher standard deviation figure, indicating more variance in period to period returns over time. The data reveal the relatively stable nature of Employment and Investment over that period; set against a background of volatile activity in ICT performance.

Table 2: Results of Descriptive Analysis

Variable	Obs	Mean	Standard Deviation	Min	Max
Employment	28	49.725	0.655	48.076	50.668
ICT	28	14.445	5.976	6.519	31.825
Investment	28	14.445	5.976	6.519	31.825

These statistics indicate that while ICT and investment are comparatively stable over time, employment shows significant fluctuations, reflecting the dynamic nature of technological development, investment and their varying impacts across different periods.

Correlation Analysis

The correlation analysis provides insights into the relationships between employment, investment, and ICT. The results show:

Table 3: Correlation analysis

Variables	(1)	(2)	(3)
(1) Employment	1.000	0.012	1.000
(2) ICT	(0.952)	-0.470	-0.425
(3) Investment	1.000	(0.012)	(0.024)

Employment size is among the variables that are weak and not significant with a correlation of 0.012($p = 0.952$). Employment vs ICT shows moderate and statistically significant negative correlation (-0.470, $p = 0.012$), i.e., as ICT increases, there is a trend for reduced of economic activity work (perhaps due to automation or substitution technology). This is what our results show; a statistically significantly negative correlation can be found between investment in ICT (−0.425, $p = 0.024$) and moderate to high levels of potential traditional investment in other areas again due to the fact that resources are directed toward advancing an individual's level of technological abilities. The negative relationship of ICT with both Employment and Investment supports its transformational effect on economic structures, causing job displacement through automation as well as influencing investment orientations. These results are in line with the results of Lastly, Chen et al. In (2023), they explored the effect of employment growth on capital accumulation in manufacturing industries in emerging countries. They revealed that although employment growth favored a greater industrial output, it was less favorable to investment relative to developed economies. This had a lot to do with the low skill level of the workforce. But in these countries the growth of manufacturing employment, especially in low-skilled labor markets, did not translate into a surge of investment in new technologies or automation.

Regression Analysis

The regression results help clarify the effects of employment, investment, and ICT on each other:

Table 4: Employment

Variables	Estimate	Standard Error	t value	Pr(>|t|)	
Employment	0.7140	0.1691	4.2230	0.0003	***
ICT	-0.0019	0.0236	-0.0790	0.9376	
Investment	0.1083	0.1556	0.6960	0.4933	
Constant	14.1369	8.5877	1.6460	0.1133	

Employment has a statistically significant positive impact on itself in the short term (estimate: 0.7140, $p = 0.0003$), indicating persistence in employment levels. Investment and ICT do not significantly affect employment, suggesting that employment in the manufacturing sector may be less sensitive to these factors.

Table 5: Information communication technology

Variables	Estimate	Standard Error	t value	Pr(>|t|)	
Employment	-3.1879	1.2917	-2.4680	0.0215	*
ICT	0.7058	0.1805	3.9110	0.0007	***
Investment	-1.1875	1.1884	-0.9990	0.3281	
Constant	164.5576	65.6107	2.5080	0.0196	*

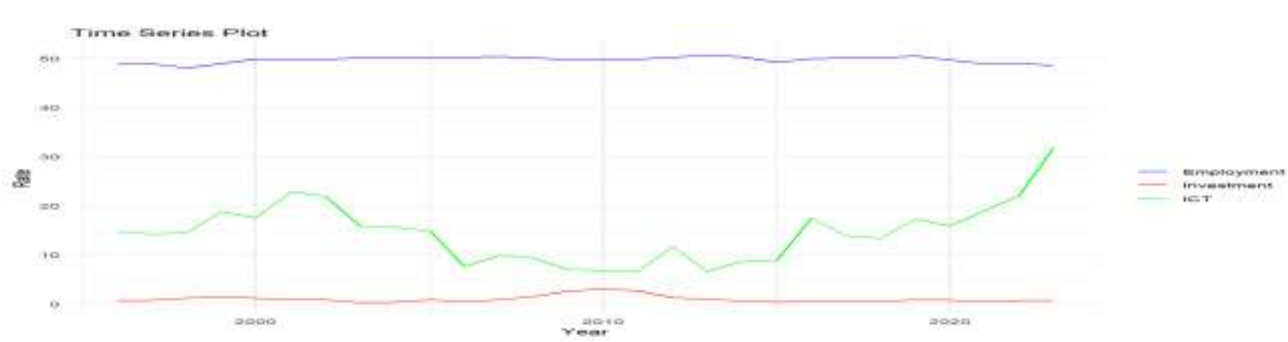
ICT has a statistically significant positive effect on itself over time (estimate: 0.7058, p = 0.0007). However, employment has a significant negative effect on ICT (estimate: -3.1879, p = 0.0215), suggesting that higher employment levels may reduce the rate of ICT adoption or investment.

Table 6: Investment

Variables	Estimate	Standard Error	t value	Pr(>|t|)	
Employment	-0.1613	0.1569	-1.0280	0.3150	
ICT	-0.0286	0.0219	-1.3060	0.2040	
Investment	0.6839	0.1443	4.7390	0.0001	***
Constant	8.7427	7.9669	1.0970	0.2840	

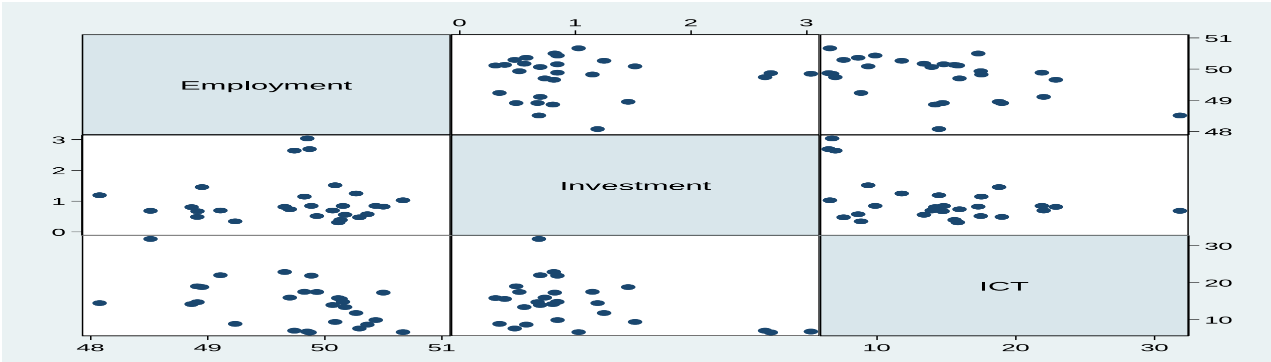
Investment shows strong persistence over time (estimate: 0.6839, p = 0.0001), while neither employment nor ICT has a statistically significant effect on investment. Butt, and Siddiqui, (2021) observed that Pakistan has been grappling with high inflation and a weakening currency, prompting the central bank to raise interest rates. While the intention is to curb inflation, high rates make borrowing more expensive. This discourages businesses from taking out loans for expansion or new ventures, limiting investment opportunities.

Figure 1: Time series Plot



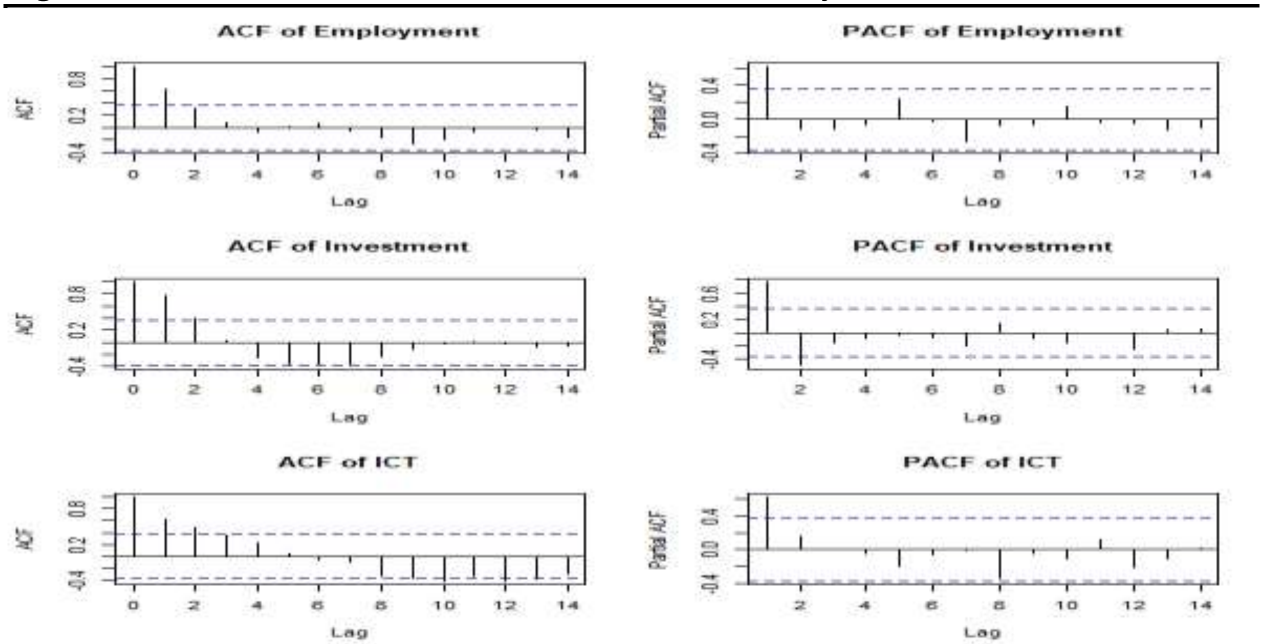
The time series plots show that employment has remained relatively stable with fluctuations, peaking around 50% in 2000 and declining in recent years. Investment shows a steady decline after 2015, and ICT exhibits a volatile pattern with significant increases from 2011 to 2020.

Figure 2: Scatter Plot Analysis



The scatter plots show-varied relationships between the variables. Employment and Investment exhibit a weak positive correlation, while Employment and ICT, as well as Investment and ICT, and show moderate relationships. The overall trend indicates that increases in one variable are not consistently associated with increases in others, especially when ICT is involved, as it may disrupt traditional trends in employment and investment.

Figure 3: Autocorrelation and Partial Autocorrelation Analysis



The results of the ACF and PACF plots were interesting. They indicated that lagged Employment, Investment and ICT have significant current values, especially for Employment. For Employment, significant correlations are seen with multiple lags in the ACF. This indicates that current Employment levels are affected by past Employment levels. The PACF shows that past values, and particularly the ones immediately preceding the current ones, are the most important. The linear ACF-curve for Investment suggests a lagged impact of past values on current investments. The PACF curve displaying the last few quarters to be significant past lags. ICT does not only show significant autocorrelations but significant ones over several lags. This implies that ICT relies heavily on the past values. Such results validate the application of time series forecasting techniques such as VAR Models.

Table 7: Covariance Matrices

Variables	Employment	Investment	ICT
Employment	0.2418	-0.0267	-0.2948
Investment	-0.0267	0.2081	-0.3717
ICT	-0.2948	-0.3717	14.1128

The covariance matrix shows that ICT exhibits the greatest variability, reflecting its rapid technological advancements. The negative correlations between ICT and both Employment (-0.2948) and Investment (-0.3717) suggest that increases in ICT may negatively affect traditional employment and investment structures, likely due to automation and the redirection of resources towards technology.

Table 8: Correlation Matrices

Variables	Employment	Investment	ICT
Employment	1.0000	-0.1000	-0.2000
Investment	-0.1000	1.0000	-0.2000
ICT	-0.2000	-0.2000	1.0000

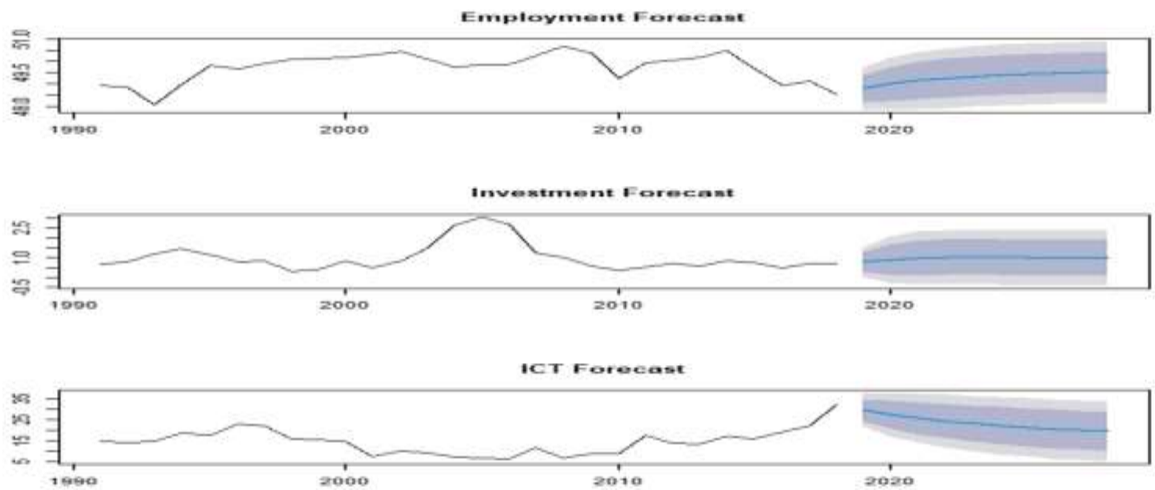
The correlations reveals that increasing ICT is associated with a slight decrease in employment (-0.2000), suggesting that automation replaces traditional jobs. Similarly, a -0.2000 correlation between Investment and ICT indicates that higher technological investments may lead to reduced traditional capital investments, signaling a shift towards tech-driven growth. Additionally, the weak negative correlation of -0.1000 between Employment and Investment shows that higher investments do not necessarily boost employment, as these investments often enhance efficiency through automation rather than job creation.

Table 9: Forecasting

Years	Employment Forecast	ICT Forecast	Investment Forecast
2024	48.7868	31.5583	0.4764
2025	48.9616	30.7386	0.2970
2026	49.0685	29.8158	0.1697
2027	49.1328	28.9748	0.0917
2028	49.1718	28.2689	0.0521
2029	49.1967	27.6932	0.0389
2030	49.2142	27.2233	0.0424
2031	49.2279	26.8319	0.0554
2032	49.2398	26.4966	0.0733
2033	49.2508	26.2008	0.0932

The forecasts provide projections for employment, investment, and ICT from 2024 to 2033. Employment is expected to increase gradually from 48.79 in 2024 to 49.25 in 2033, signaling a slow but steady rise in job opportunities in the manufacturing sector. ICT is forecasted to decline consistently, which could suggest either a reduction in ICT-related activities or a shift in focus away from traditional ICT measures in the sector. However, investment is forecasted to decline until 2029 before recovering slightly by 2033, which may point to potential economic challenges.

Figure 4: Forecasting plot



The anticipated series of econometric models provide employment, investment and ICT over the period 1990–2025 appears to present some peculiar characteristics. The chart above also tells that the employment began to recover itself after 2020. The constant however is different for Economy which changed very slightly over long time but is more volatile in the short term as compared to the Investment. The most dominant, being the ICT has a negative slope and its volatility increases after year 2020. The decline could be due alteration in the direction of ICT investment flow or could mean that the ICT industry is now mature and only viable growth is a challenge. By and large, as time moves forward, the broader the confidence intervals around the point forecasts, the less reliable they are for predicting future events — they become less dependable with different economic scenarios, changing policies or new technologies being introduced. As a result, the distant future seems to be uncertain for advanced timed forecasts with a view of more than half of the wavelengths. It requires more drastic measures in such situations.

Discussion

The findings highlight the intricate relationship between technology and labor in the manufacturing industry. As ICT advances productivity and efficiency, it simultaneously diminishes the necessity for manual labor, resulting in a decline in job opportunities. This transition is evidenced by the moderate negative correlations between ICT and employment, as well as between ICT and investment. Huang and Zhang (2017) examined the fact that the growth of the ICT sector leads to the modernization of the industry and job creation in high-skilled sectors. On the other hand, such modernization also aggravates the problems of job loss for low-skilled workers in the traditional manufacturing sector. As companies allocate greater resources to technology, they may diminish investments in conventional capital expenditures, thereby further influencing the labor market. Investment, although crucial for economic expansion, does not seem to substantially affect the pace of ICT adoption or job creation. This finding indicates that, in the absence of targeted policies to promote the alignment of investment with employment growth, the manufacturing sector may persist in encountering difficulties in reconciling technological advancement with job creation. The anticipated reduction in ICT investment raises apprehensions regarding the long-term viability of technological advancement in the manufacturing sector. Should ICT investment persist in declining, the sector may encounter challenges in sustaining competitiveness and productivity within the global market. Choi, Dutz, and Usman (2020) looked at the relationships between ICT and employment for manufacturing industries and their study reveals that the positive effects of this ICT on employment were dependent on how skilled the workers were. And in the regions with low employment of that kind of skill, the advantages of more ICTs were limited and even led to downsizing of workforce rather than exploiting further utilization of workforce.

Conclusion

The examination of employment, investment, and ICT within the manufacturing sector indicates that, although employment remains comparatively stable, ICT exerts a significant adverse effect on both employment and investment. Study of Lee and Kim (2018) supported this study that a decrease in low-skill employment. The results demonstrate that progress in ICT has led to job displacement, presumably due to automation, which supplants conventional positions in the sector. Investment, while consistently sustained, exerts limited impact on employment or ICT, indicating that although capital investment is essential for growth, it may not directly lead to job creation. This study is in line with the study of Feldstein (2021) which stated that actual or anticipated developments in employment matter for investment decisions because they impact the expansion of capacities and the competitive performance of related industries. Ali and Qureshi (2019) also supported how job creation influences infrastructure investment in the manufacturing sector. The projections indicate a gradual rise in employment, accompanied by a decrease in both investment and ICT, suggesting possible challenges for the sector's future.

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