Volume: 5
Issue: 1 (2026)
Pages: 129–140
ISSN (Online): 3006-6646
DOI: 10.62843/jrsr/2026.5a177

JRSR
JOURNAL OF REGIONAL STUDIES REVIEW

Cite this Article: Sattar, I., Haq, M. A. A., Faridi, M., Z., & Mehmood, K. A. (2026). Digital Technology Adoption, Financial Development and Unemployment in Pakistan. *Journal of Regional Studies Review, 5*(1), 129-140. https://doi.org/10.62843/jrsr/2026.5a177

RESEARCH ARTICLE JOURNAL OF REGIONAL STUDIES REVIEW (JRSR)

Digital Technology Adoption, Financial Development and Unemployment in Pakistan

Iram Sattar [a] M Ashraf Al Haq [b] Muhammad Zahir Faridi [c] Khawaja Asif Mehmood [d]

Corresponding Author: M Ashraf Al Haq; mashrafalhaq_bua@lus.ac.bd

Abstract: The rapid expansion of digital technologies has transformed labor markets worldwide, raising important questions about their implications for employment in developing economies. This study investigates the impact of digital technology adoption on the unemployment rate in Pakistan over the period 1993–2024. Digital technology adoption is proxied by internet usage, while GDP per capita, gross fixed capital formation, and inflation are included as control variables. Using annual time-series data from the World Development Indicators, the study employs the Auto-Regressive Distributed Lag (ARDL) bounds testing approach to examine both long-run and short-run relationships among the variables. The results confirm the existence of a long-run co integrating relationship. Long-run estimates indicate that digital technology adoption, FDI and GDP per capita significantly reduce unemployment in Pakistan. The findings suggest that digitalization, when supported by growth-oriented and inclusive policies, can contribute to unemployment reduction in Pakistan. The study offers policy-relevant insights for promoting digital inclusion, skill development, and employment generation in developing economies.

Keywords: Digital Technology, Internet Usage, Unemployment, ARDL, Pakistan, Labor Market

Introduction

The role that technological change has traditionally played in the economic structure and labor market performance has been decisive in terms of the productivity, labor market outcome, and skill demand in the different economies (Schumpeter, 1942; Solow, 1957). The use of digital technology in the last several decades, including the spread of the internet, the use of information and communication technologies (ICT), and online platforms, has become one of the key drivers of the changes in the nature of work and employment on the global scale (Brynjolfsson& McAfee, 2014; Autor, 2015). Although digitalization has increased the employment opportunities and made it possible to create new jobs, it has also created issues related to job displacement, unemployment caused by changes in technology, and growing inequalities in the labor market in particular in developing countries (Acemoglu & Restrepo, 2020).

The connection between the use of digital technology and unemployment is theoretically not clear. On a positive aspect, the digital technologies are likely to increase productivity, create innovation, and create jobs by establishing new industries and jobs (Romer, 1990; Aghion & Howitt, 1992). The access to the Internet helps to improve information flows, decreases the expenses of job-searching and increases the efficiency of matching the labor market that potentially lowers the unemployment rates (Chatha et al., 2025; Kuhn & Mansour, 2014). The digital platforms and online freelancing also increase employment opportunities as it enables workers to access the global labor markets, especially in developing economies (Grahamet al., 2017).

[a] PhD Economics (Scholar), School of Economics, Bahauddin Zakariya University, Multan, Punjab, Pakistan.
[b] Assistant Professor, Leading University, Sylhet, Bangladesh.
[c] Professor of Economics, School of Economics, Bahauddin Zakariya University, Multan, Punjab, Pakistan.
[d] Assistant Professor of Economics, School of Economics, Bahauddin Zakariya University, Multan, Punjab, Pakistan.

On the other hand, pessimistic views state that digitalization can cause displacement of labor through automation of routine and low-skill labor reducing demand of labor in conventional industries (Autoret al., 2003; Acemoglu & Autor, 2011). The technological change is skill-biased, which suggests that employees with low digital skills might become more vulnerable to unemployment, whereas the benefits will be distributed disproportionately to skilled laborers (Goldin& Katz, 2008). Consequently, the overall impact of the digital technology adoption on employment will be determined by the institutional framework in a given country, education system, and an ability to adjust to the technological change (Cirilloet al., 2021).

Structural limitations that impede these dynamics in developing countries include the lack of digital infrastructure, unequal access to technology, and informality (UNCTAD, 2018; ILO, 2021). Although digital technologies show potential in terms of creating jobs, particularly by means of entrepreneurship and self-employment, they can also contribute to the reinforcement of existing disparities in case the access to digital possibilities is not even (Qureshi, 2014; World Bank, 2016). As a result, it is necessary to conduct country-level empirical analysis to determine the interaction between digital adoption and unemployment within definite socioeconomic circumstances.

The case of Pakistan provides a pertinent example to such concerns. The country has recorded substantial growth in the adoption of digital technologies over the last 30 years, which is demonstrated by the increase in internet penetration, mobile penetration, and the growth of the digital services sector (Pakistan Telecommunication Authority, 2022; World Bank, 2023). Online freelancing has also become one of the most popular countries for online freelancing, which offers new sources of income to skilled laborers and young people (Kässi & Lehdonvirta, 2018). Even with these developments, the issue of unemployment, particularly among young people and people with a high level of education, has become a long-term problem because of the high population growth, lack of skills, and the creation of jobs in the formal sector (Amjad & Awais, 2016).

The presence of increasing digital use and stable unemployment present essential concerns regarding the success of digital transformation in finding solutions to labor market issues in Pakistan. Though digital technologies can open new job opportunities, they can also substitute the workforce in the traditional fields or marginalize the employees who are not skilled in digital technologies (Nasir, 2018; Malik, 2020). Furthermore, the advantages of digitalization can be disproportionately concentrated in the regions, genders, and skills, which can deepen the gap in the labor market (Siddiqui & Rehman, 2017).

There is mixed empirical evidence on the nexus between digitalization and unemployment. Increased internet use and ICT development minimizes unemployment by increasing productivity and efficiency in the labor market (Czernich et al., 2011), whereas some studies have neutral or negative outcomes of automation and labor substitution (Graetz & Michaels, 2018; Dauth et al., 2021). With regard to Pakistan, the literature has not been extensive in terms of time series studies that would assess the overall effect of digital technology adoption on unemployment (Hussain & Mahmood, 2019).

Keeping in view the discussion, the current paper analyzeshow adoption of digital technology influences the unemployment rate in Pakistan between the years 1993 and 2024. The study adds to the literature by offering evidence country-specific to a developing economy that is going through a digital transformation (through the use of time-series econometric approach). The results are promised to provide valuable policy implications to digital inclusion, skill development, and labor market reforms to utilize the digital technologies in order to decrease the unemployment rates and provide inclusive economic growth.

Literature Review

Unemployment is a multifaceted socio-economic challenge influenced by macroeconomic, demographic, institutional, and external factors. A substantial body of empirical literature has examined the determinants of unemployment across developed and developing economies, revealing both converging and conflicting findings depending on country context, methodology, and time period.

A number of studies contend that digital technology is contributing to more unemployment, especially among low-skilled employees. Acemoglu & Restrepo (2020) discovered that the introduction of industrial robots to the United States substituted regular jobs, causing an increase in the local unemployment rates. On the same note, Frey & Osborne (2017) approximated that a significant portion of the employment is vulnerable to automation and that this is in the manufacturing and clerical jobs. Dachs et al., (2019) demonstrated that in the short term, digitalization increases unemployment because of the mismatch of skills and costs of adaptation, notwithstanding that productivity increases in the long-term perspective. Other findings according to Marjanović et al., (2018) also showed that technological innovation also augmented structural unemployment in transition economies. Other research, on the other hand, indicates that the digital technology lowers the rate of unemployment by generating new employment opportunities. According to Autor (2015), even though automation substitutes some jobs, it also creates other jobs and supplements human work. Bessen (2019) discovered that computerization boosted the number of jobs in the fields where technology promoted the productivity of the workers. Hjort & Poulsen (2019) showed that the expansion of the broadband internet in developing economies had a significant impact on the reduction of unemployment by enhancing the productivity of firms and matching labor markets.

Moreover, numerous variables also influence the unemployment including empirical evidence provided by Jordan (Al-Freijat & Hammouri, 2022), Pakistan (Ahmad et al., 2017; Abbas, 2014), Africa (Tsaurai, 2020) indicate that the GDP growth increases job opportunities. In the same vein, research dedicated to foreign direct investment (FDI) demonstrates that FDI lowers the level of unemployment through an increase of productive capacity and an increase of labor demand (Mazher et al., 2020; Zeb et al., 2014). Unemployment in some countries such as Bahrain and Jordan also had a negative correlation with domestic investment and gross fixed capital formation (Alrabba, 2017; Alrayes & Wadi, 2018). These conclusions emphasize the need of growth-oriented and investment friendly policies towards creation of employment.

Conversely, some of the studies show that there are other macroeconomic and external factors which raise unemployment. One of the most stable causes of unemployment increase can be the population growth, especially in developing nations when creating employment falls behind population growth (Alabed et al., 2022; Obayori & Udeorah, 2020; Maijama et al., 2019). The volatility of the exchange rate has been also observed to negatively affect unemployment in Nigeria, Bangladesh, and Morocco since the depreciation of their currencies increases the cost of production and decreases labor demand (Ani et al., 2019; Islam & Sahajalal, 2019). Also, it is said that external debt drives unemployment by pushing out productive investment and raising macroeconomic instability (Evans, 2022; Cahyadin & Ratwianingsih, 2020).

There is little empirical research in Pakistan about the nexus of digitalization, and unemployment in the context of the country. The available literature is often interested in sectoral results, productivity, or growth impact instead of aggregate unemployment dynamics. There is a gap in the literature as time-series studies of the long-run relationship between internet use and unemployment are especially scarce. It is important to note that given the demographic pressures and the current process of digital transformation in Pakistan, this relation is important to the policy making that is evidence-based.

Data, Theoretical Framework, and Methodology

This paper uses the secondary sources of data in order to examine the effects of the adoption of digital technology on unemployment in Pakistan. The data sources are the World Bank data on World Development Indicators (WDI) which is a reliable and internationally comparable macroeconomic data. The research paper covers a thirty-one-year time-period, i.e., 1993-2024, to conduct the annual time-series observations.

The dependent variable is the unemployment rate (UEMP). The use of digital technology is also proxied by the use of internet by individuals (DT), which is the main independent variable. GDP per capita (GDPPC), financial development (FD), foreign direct investment (FDI), gross fixed capital formation (GFCF) and the consumer price index (INF) are added as control variables to ensure that they control the rest of the macroeconomic conditions and eliminate the bias of omitted variables. GDP per capita measures the growth and income levels in the economy, gross capital formation is a measure of investment in the economy and CPI is a measure of inflationary pressures in the economy.

Functional Form of the Model

$$UEMP = f(DT, GDPPC, GFCF, INF, FD, FDI)$$

Econometric Form of the Model

$$\text{UEMP}= \beta_o + \beta_1 DT_t + \beta_2 GDPPC_t + \beta_3 GFCF_t + \beta_4 INFC_t + \beta_5 FD_t + \beta_6 FDI_t + u_t$$

General Form Equation of Model

$$\begin{aligned}\Delta(UEMP)_t &= \alpha + \beta_1(DT)_{t-1} + \beta_2(GDPPC)_{t-1} + \beta_3(GFCF)_{t-1} + \beta_4(INF)_{t-1} + \beta_5(FD)_{t-1} + \beta_6(FDI)_{t-1} \\ &+ \sum_{i=1}^{a_1} \delta_1 \Delta(DT)_{t-i} + \sum_{i=0}^{a_2} \delta_2 \Delta(GDPPC)_{t-i} + \sum_{i=0}^{a_3} \delta_3 \Delta(GFCF)_{t-i} + \sum_{i=0}^{a_4} \delta_4 \Delta(INF)_{t-i} \\ &+ \sum_{i=0}^{a_5} \delta_5 \Delta(FD)_{t-i} + \sum_{i=0}^{a_6} \delta_6 \Delta(FDI)_{t-i} + \varepsilon_t\end{aligned}$$

Long Run Equation of Model

$$\begin{aligned}\Delta(UEMP)_t &= \alpha + \sum_{i=1}^{a_1} \eta_1 (DT)_{t-i} + \sum_{i=0}^{a_2} \eta_2 (GDPPC)_{t-i} + \sum_{i=0}^{a_3} \eta_3 (GFCF)_{t-i} + \sum_{i=0}^{a_4} \eta_4 (INF)_{t-i} \\ &+ \sum_{i=0}^{a_5} \eta_5 (FD)_{t-i} + \sum_{i=0}^{a_6} \eta_6 (FDI)_{t-i} + \varepsilon_t\end{aligned}$$

ECM Equation of Model is

$$\begin{aligned}\Delta(UEMP)_t &= \alpha + \sum_{i=1}^{a_1} \lambda_1 \Delta(DT)_{t-i} + \sum_{i=0}^{a_2} \lambda_2 \Delta(GDPPC)_{t-i} + \sum_{i=0}^{a_3} \lambda_3 \Delta(GFCF)_{t-i} + \sum_{i=0}^{a_4} \lambda_4 \Delta(INF)_{t-i} \\ &+ \sum_{i=0}^{a_5} \lambda_5 \Delta(FD)_{t-i} + \sum_{i=0}^{a_6} \lambda_6 \Delta(FDI)_{t-i} + \partial ECM_{t-1} + \varepsilon_t\end{aligned}$$

Where $UEMP_t$ is the unemployment rate, DT_t is the digital technology, $GDPPC_t$ is the GDP per capita, $GFCF_t$ is the gross fixed capital formation, INF_t is the inflation rate, FD is financial development and FDI represents foreign direct investment. β_0 indicates the intercept, β_1–β_4 are the coefficients of independent variables and ε_t is the error term.

Where $UEMP_t$ is the unemployment rate, DT_t is the digital technology, $GDPPC_t$ is the GDP per capita, $GFCF_t$ is the gross fixed capital formation, INF_t is the inflation rate, FD is financial development and FDI represents foreign direct investment. β_0 indicates the intercept, β_1–β_4 are the coefficients of independent variables and ε_t is the error term.

Table 1

Data Description

Variable	Notation	Measurement Description	Source
Unemployment Rate	UEMP	Percentage of the labor force that is unemployed but actively seeking employment	World Bank WDI
Digital Technology	DT	Percentage of the population using the internet; proxy for digital technology adoption	World Bank WDI
Gross Fixed Capital Formation	GFCF	Total value of new fixed assets such as machinery, equipment, and infrastructure; ratio scale	World Bank WDI
GDP per capita	GDPPC	Gross domestic product divided by total population; indicator of economic growth and income level; ratio scale	World Bank WDI

Variable	Notation	Measurement Description	Source
Inflation Rate	INF	Consumer price index measuring average price changes of a basket of goods and services; indicator of inflation	World Bank WDI
Financial Development	FD	Domestic credit to private sector as a percentage of GDP	World Bank WDI
Foreign Direct Investment	FDI	FDI as a percentage of GDP	World Bank WDI

Econometric Methodology

The analysis starts with descriptive statistics that analyzes the dispersion and central tendency of the variables. The direction and the strength of the relationships between the variables are then evaluated through Pearson correlation analysis.Since the data is time series in nature, the properties of unit roots are investigated by means of an Augmented Dickey-Fuller (ADF) test (at levels and first difference). This is done to establish the sequence of integration of every variable. By use of the fact that the variables are combined at I(0) and I(1), Auto-Regressive Distributed Lag (ARDL) bounds testing method suggested by Pesaran et al. (2001) works best.The ARDL bounds test is applied to test the presence of the long run cointegration relationship amongst the unemployment, internet usage, and the control variables. After cointegration has been established the long-run coefficients, as well as the short-run dynamics are estimated using, ARDL error correction model (ECM).

Data Analysis

The descriptive statistics of the variables are indicated in Table 2. The mean values of UEMP, DT, GDPPC, INF, GFCF, FD and FDI 4.402, 8.823, 976.901, 9.514, 14.630, 20.395 and 1.021, respectively. The maximum values of UEMP, DT, GDPPC, INF, GFCF, FD and FDI are 7.830, 28.304, 1569.338, 30.768, 19.112, 28.734 and 3.668, respectively. The skewness value of variables indicates that DT, INF, FD, FDI and GFCF are skewed positively while UEMP and GDPPC are negatively skewed. The distributions of the variables UEMP, DT, GDPPC and FD are platykurtic with a kurtosis of less than 3 with exception of INF, FDI and GFCF which is leptokurtic.

Table 2

Descriptive Statistics

	Mean	Maximum	Minimum	S. D.	Skewness	Kurtosis
UEMP	4.402	7.830	0.398	2.431	-0.357	1.912
DT	8.823	28.304	0.000	8.296	0.874	2.912
GDPPC	976.901	1569.338	399.956	405.875	-0.097	1.555
INF	9.514	30.768	2.529	5.904	1.631	6.612
GFCF	14.630	19.112	11.457	1.725	0.677	3.040
FD	20.395	28.734	14.363	4.767	0.149	1.502
FDI	1.021	3.668	0.207	0.837	2.022	6.309

Table 3 presents the correlation matrix of variables. The outcomes show that unemployment rate is negatively correlated with the DT (-0.054), GDPPC (-0.223), INF (-0.115), GFCF (-0.247), FD (-0.143), and FDI (-0.516).

Table 3

Correlation Matrix

	UEMP	DT	GDPPC	INF	GFCF	FD	FDI
UEMP	1.000						
DT	-0.054	1.000					

	UEMP	DT	GDPPC	INF	GFCF	FD	FDI
GDPPC	-0.223	0.872	1.000				
INF	-0.115	0.441	0.192	1.000			
GFCF	-0.247	-0.632	-0.580	-0.012	1.000		
FD	-0.143	-0.723	-0.757	-0.033	0.666	1.000	
FDI	-0.516	-0.279	-0.184	0.075	0.447	0.701	1.000

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are used to determine the stationarity of the data. The outcomes show that UEMP, DT, FD, FDI, and GDPPC are stationary to first difference I(1) and GFCF and INF are stationary to level I(0). The combination of these integration orders proves the ARDL approach to the analysis.

Table 4

Unit Root Test

Variables	ADF t-Stat	Prob	Integration	PP t-Stat	Prob	Integration
UEMP	-5.715	0.002	I(1)	-5.124	0.000	I(1)
DT	-5.085	0.004	I(1)	-5.512	0.001	I(1)
GDPPC	-6.319	0.029	I(1)	-6.258	0.000	I(1)
GFCF	-3.115	0.000	I(0)	-3.024	0.000	I(0)
INF	-2.725	0.021	I(0)	-2.765	0.000	I(0)
FD	-4.366	0.001	I(1)	-4.467	0.001	I(1)
FDI	-3.724	0.000	I(1)	-3.460	0.000	I(1)

The ARDL bounds test proves the presence of a long-run cointegrating relationship between the variables. The F-ratio is greater than the upper limit at the 5% level hence confirms the existence of long-run relationship between UEMP, DT, GDPPC, INF, FD, FDI, and GFCF.

Table 5

ARDL Bounds Test

F-Statistic	Significance	I(0)	I(1)
6.724	10%	2.45	3.52
	5%	2.86	4.01
	2.5%	3.25	4.49
	1%	3.74	5.06
K		4	

Table 6 presents the long-run ARDL model results. The results show that GDP per capita (GDPPC) has a negative and statistically significant coefficient, indicating that higher income levels and economic growth contribute to reducing unemployment. This supports the view that growth-driven expansion increases labor demand and improves job creation in the economy (Mandel & Liebens, 2019; Hassan & Nassar 2015). GFCF shows a negative but statistically insignificant effect on unemployment. This suggests that investment in physical capital does not significantly translate into employment generation. Such a result may reflect capital-intensive investments, structural rigidities, or time lags between investment and labor absorption in Pakistan. Digital technology has a strong positive and significant impact on unemployment. This indicates that digitalization helps reduce unemployment by enhancing productivity, enabling new job opportunities, and improving labor market efficiency through digital platforms (Ivanitskaia, 2022; Gavrilescu, 2025). The inflation rate also exhibits a significant negative relationship with unemployment, consistent with the short-run Phillips curve hypothesis, where rising inflation is associated with increased economic activity and lower unemployment (Omran & Bilan, 2021). The FD related long run coefficient is found to be insignificant. The result of FDI has a statistically significant and negative impact on the unemployment rate, implying that increased FDI contributes to employment generation (Johnny et al., 2018). Financial development also exhibits a negative coefficient, but its effect is statistically insignificant, indicating a limited role in reducing unemployment.

Table 6

Long-Run Analysis

Dependent Variable: UEMP				
Selected Model: ARDL(1, 1, 1, 1, 2, 0, 0)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
GDPPC	-0.0124	0.0017	-7.2430	0.0000
GFCF	-0.0167	0.2231	-0.0748	0.9413
DT	0.5884	0.0982	5.9919	0.0000
INF	-0.3606	0.0703	-5.1313	0.0001
FD	-0.0719	0.1239	-0.5803	0.5693
FDI	-1.2976	0.5155	-2.5172	0.0222
C	18.4297	4.5366	4.0625	0.0008

Table 7 presents the short-run error correction form of ARDL model. The coefficient of Error Correction Model (ECM) is negative and statistically significant thus confirms the existence of a stable long-run relationship. It indicates that approximately 92% of short-run disequilibrium in unemployment is corrected each period, implying rapid adjustment toward long-run equilibrium.

Table 7

Short-Run ECM Model Analysis

Dependent Variable: UEMP				
Selected Model: ARDL(1, 1, 1, 1, 2, 0, 0)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(GDPPC)	-0.0101	0.0050	-2.0010	0.0616
D(GFCF)	0.4702	0.3833	1.2268	0.2366
D(DT)	-0.1585	0.4728	-0.3353	0.7415
D(INF)	-0.0120	0.0539	-0.2234	0.8259
D(INF)	0.1624	0.0785	2.0701	0.0540
D(FD)	-0.0803	0.1397	-0.5749	0.5729
D(FDI)	-1.4492	0.5076	-2.8550	0.0110
ECM	-0.9168	0.2265	-4.0498	0.0001

Different model diagnostic tests are applied in this study. The model is robust as all diagnostic checks have been passed. The Breusch Godfrey LM test indicates the absence of autocorrelation, Breusch Pagan/Whites tests indicate the absence of heteroskedasticity, and Jarque-Bera test indicates that it is normal. CUSUM and CUSUM of squares plot show that the model is stable at the level of 5 percent.

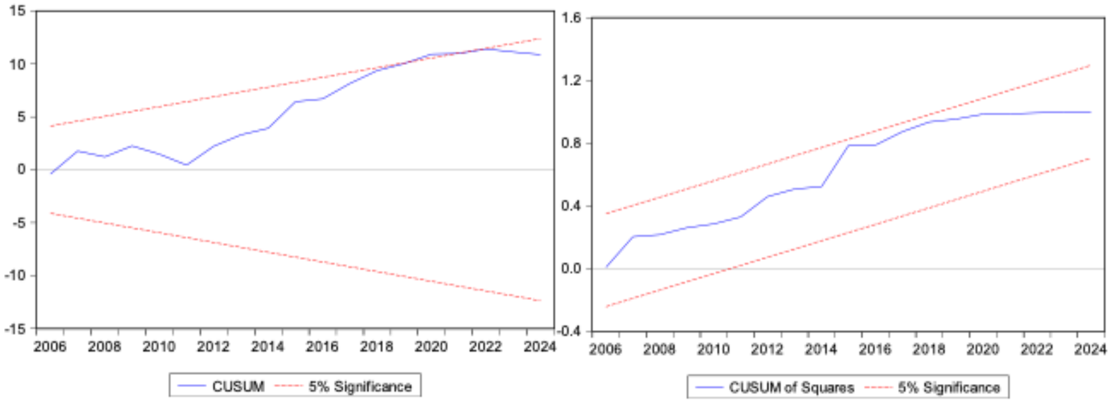
Table 8

Diagnostic Tests

Test	**Statistic**	**Prob.**	**Result**
Normality (Jarque-Bera)	0.432	0.644	Residuals are normally distributed
Serial Correlation LM	1.955	0.731	No autocorrelation

Heteroskedasticity Test	0.466	0.821	No heteroskedasticity

Figure 1
Model Stability Test



Conclusions

This study examined the impact of digital technology adoption on unemployment in Pakistan over the period 1993–2024 using an ARDL modeling framework. The empirical results prove that there is a long-run relationship between unemployment, digital technology, GDPPC, GFCF, FDI, FD and inflation rate. The long-term implications indicate that the use of digital technology, which is indicated by the use of the internet, has a significant impact on lowering the rate of unemployment in Pakistan. This implies that digitalization has had a positive impact on the performance of labor markets by increasing productivity, widening access to information, job matching, and innovation of new jobs through freelance services, online services, and internet entrepreneurship. The GDP per capita also has a negative and statistically significant impact on unemployment, which explains the role of job creation through growth in the Pakistani labor market. The negative correlation between inflation and unemployment is significant, which confirms the short-run Phillips curve theory and that moderate inflation can be a catalyst to the economic activity and the labor demand. Nevertheless, gross fixed capital formation is observed to be statistically insignificant implying that investment in Pakistan has been capital intensive or is restricted by structural rigidities which restrict its short-term employment-creating capacity. The results also show that FDI has a statistically significant and negative impact on the unemployment rate, implying that increased FDI contributes to employment generation. Financial development also exhibits a negative coefficient, but its effect is statistically insignificant, indicating a limited role in reducing unemployment.The short-run ECM findings also confirm the long-run equilibrium by the presence of a significant and negative error correction term which demonstrates a very fast adjustment to equilibrium following a short run shock. The results indicate that digital transformation with the accompanying economic growth can be a useful tool of minimizing unemployment in Pakistan. The research adds to the time-series gaps on the digitalization and the labor market performance of developing economies and offers a solution to policy-makers interested in inclusive and sustainable growth in employment.

Implications of the Study

This study has significant policy implications on Pakistan. First, the high level of unemployment-reducing is an important impact of digital technology, and it is necessary to increase the digital infrastructure, availability, and affordability of the internet, especially in the rural and undeveloped parts of the world. Second, there are important policies that emphasize on developing digital skills, professional training, and education based on computers and information technologies so that the labor force can be in a position to utilize effective technological development. Third, the GDP per capita negative effects on unemployment indicate that macroeconomic policies that focus on growth must be coordinated with employment creation policies. Besides, the minor role of capital formation suggests that investment policies must focus on the labor intensive and technology based sectors instead of being capital intensive projects. Lastly, policymakers ought to come up with inclusive digital labor market policies to safeguard gig and freelance workers.

Limitations of the Study

This study has some limitations.First, the adoption of digital technology is proxied by the use of internet only, and this might not be a fully multidimensional measure of digitalization, including automation, artificial intelligence, or work based on platforms. Second, time-series analysis is based on aggregate time-series information, which can obscure sectoral, regional and skill level disparities in the impact of unemployment. Third, the ARDL methodology detects relationships without exhausting the possible endogeneity or causality problems. Lastly, there is not an explicit model of institutional factors including the quality of labor market regulations and education and informality. The future study can address the shortcomings of the current study through the use of disaggregated data, other digitalization indicators, and more complex econometric methods to shed more light on the subject.

References

Abbas, S. (2014). Long term effect of economic growth on unemployment level: In case of Pakistan. *Journal of Economics and Sustainable Development*, *5*(11), 103-108.

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of Labor Economics* (pp. 1043–1171). Elsevier.

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *The Journal of Political Economy*, *128*(6), 2188–2244. https://doi.org/10.1086/705716

Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, *60*(2), 323. https://doi.org/10.2307/2951599

Ahmad, W., Yan, T., Zahoor., Begum, M., Bibi, A., & Bibi, M. (2017). Determinants of Unemployment in Pakistan. *Specialty Journal of Accounting and Economics,* 3(2), 74-82. https://sciarena.com/article/determinants-of-unemployment-in-pakistan

Al-Freijat, S. Y., & Hammouri, Q. (2022). The Impact of Economic Growth on Unemployment in Jordan during the period 1980-2022. *Central European Management Journal*, *30*(4), 1384-1391. https://doi.org/10.57030/23364890.cemj.30.4.139

Alabed, Q. M. Q., Said, F. F., Karim, Z. A., Zaidi, M. A. S., & Mansour, M. (2022). Determinants of unemployment in the MENA region: New evidence using dynamic heterogeneous panel analysis. In *The 8th International Conference on Advanced Machine Learning and Technologies and Applications (AMLTA2022)* (pp. 401–411). Springer International Publishing.

Alrabba, M. I. M. (2017). The determinants of unemployment rate in Jordan: a multivariate approach. *International Journal of Economics and Finance*, *9*(11), 109-117. https://doi.org/10.5539/ijef.v9n11p109

Alrayes, S. E., & Abu Wadi, R. M. (2018). Determinants of unemployment in Bahrain. *International Journal of Business and Social Science*, *9*(12). https://doi.org/10.30845/ijbss.v9n12p8

Amjad, R., & Awais, M. (2016). Structural unemployment in Pakistan: Causes and policy remedies. *Pakistan Development Review*, *55*(3), 255–275.

Ani, E. C., Joel, E., & Baajon, M. A. (2019). Exchange rate and unemployment in Nigeria: An analysis. *International Journal of Family Business and Management*, *3*(2), 1-7. https://doi.org/10.15226/2577-7815/3/2/00129

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *The Journal of Economic Perspectives: A Journal of the American Economic Association*, *29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3

Autor, D., Levy, F., & Murnane, R. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics,* *118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Cahyadin, M., & Ratwianingsih, L. (2020). External debt, exchange rate, and unemployment in selected ASEAN countries. *Jurnal Ekonomi & Studi Pembangunan*, *21*(1). https://doi.org/10.18196/jesp.21.1.5029

Chatha, I. Y., Batool, S. A., Hussain, S., &Asghar, M. M. (2025). Revealing the Role of Technological Innovation, Institutional Quality and Foreign Direct Investment in Impacting Human Development in Developing Countries: Insights from FGLS and PCSE Models. *The Critical Review of Social Sciences Studies*, *3*(1), 223-242.

Cirillo, V., Evangelista, R., Guarascio, D., & Sostero, M. (2021). Digitalization, routineness and employment: An exploration on Italian task-based data. *Research Policy*, *50*(7), 104079. https://doi.org/10.1016/j.respol.2020.104079

Czernich, N., Falck, O., Kretschmer, T., & Woessmann, L. (2011). Broadband infrastructure and economic growth. *The Economic Journal*, *121*(552), 505-532. https://doi.org/10.1111/j.1468-0297.2011.02420.x

Dachs, B., Kinkel, S., & Jäger, A. (2019). Bringing it all back home? Backshoring of manufacturing activities and the adoption of industry 4.0 technologies. *Journal of World Business*, *54*(6), 101017. https://doi.org/10.1016/j.jwb.2019.101017

Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2018). Adjusting to robots: Worker-level evidence. https://doi.org/10.21034/iwp.13

Evans, Y. (2022). The effect of external debt, unemployment rate, and inflation on economic growth in Ghana. *Journal of Empirical Studies*, *9*(2), 24-34. https://doi.org/10.18488/66.v9i2.3178

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254-280. https://doi.org/10.1016/j.techfore.2016.08.019

Gavrilescu, I. (2025). Digitalization and its implications on unemployment. *Proceedings of the International Conference on Business Excellence*, *19*(1), 4546-4556. https://doi.org/10.2478/picbe-2025-0347

Graetz, G., & Michaels, G. (2018). Robots at work. *The Review of Economics and Statistics*, *100*(5), 753-768. https://doi.org/10.1162/rest_a_00754

Graham, M., Hjorth, I., & Lehdonvirta, V. (2017). Digital labour and development: Impacts of global digital labour platforms and the gig economy on worker livelihoods. *Transfer: European Review of Labour and Research*, *23*(2), 135-162. https://doi.org/10.1177/1024258916687250

Hassan, M., &Nassar, R. (2015). Effects of debt and gdp on the unemployment rate: an empirical study. *Journal of International Business Disciplines*, *10*(2), 218-230.

Hjort, J., & Poulsen, J. (2019). The arrival of fast Internet and employment in Africa. *American Economic Review*, *109*(3), 1032–1079. https://doi.org/10.1257/aer.20161385

Hussain, I., &Mahmood, H. (2019). ICT, institutional quality, and economic growth in Pakistan. *Pakistan Journal of Commerce and Social Sciences, 13*(1), 87–106.

Islam, M. S., & Sahajalal, M. (2019). An empirical study of GDP, exchange rate, inflation and unemployment in Bangladesh. *International Journal of Multidisciplinary Research and Development*, *6*(6), 51-53.

Ivanitskaia, V. (2022). The impact of digitalization on unemployment. *Proceedings of the European Union's Contention in the Reshaping Global Economy*, 55-67. https://doi.org/10.14232/eucrge.2022.4

Johnny, N., Timipere, E. T., & Krokeme, O. (2018). Impact of foreign direct investment on unemployment rate in Nigeria (1980-2015). *International Journal of Academic Research in Business and Social Sciences*, *8*(3). https://doi.org/10.6007/ijarbss/v8-i3/3905

Kässi, O., & Lehdonvirta, V. (2018). Online labour index: Measuring the online gig economy for policy and research. *Technological Forecasting and Social Change*, *137*, 241-248. https://doi.org/10.1016/j.techfore.2018.07.056

Kuhn, P., & Mansour, H. (2014). Is internet job search still ineffective? *The Economic Journal*, *124*(581), 1213-1233. https://doi.org/10.1111/ecoj.12119

Maijama'a, R., Musa, K. S., Yakubu, M., & Mohammed, N. (2019). Impact of population growth on unemployment in Nigeria: Dynamic OLS approach. *Journal of Economics and Sustainable Development*, *10*(22), 79-89. https://doi.org/10.7176/jesd/10-22-09

Malik, A. (2020). Digital skills gap and unemployment in Pakistan: Challenges and opportunities. *Journal of Social Sciences, 14*(2), 112–125.

Mandel, C., & Liebens, P. (2019). The relationship between GDP and unemployment rate in the U.S. *International Journal of Business and Social Science*, *10*(4). https://doi.org/10.30845/ijbss.v10n4p3

Marjanović, V., et al. (2018). Technological change and unemployment. Technological Forecasting and Social Change, 129(2), 137–145.

Mazher, M., Mukhtar, T., & Sohail, S. (2020). Impact of foreign direct investment and foreign remittances on unemployment in Pakistan: A time series analysis. *IIIE Journal of Economics and Finance*, *1*(1), 66-83.

Nasir, S. (2018). ICT, human capital and unemployment: Evidence from Pakistan. *Dialogue (Pakistan), 13*(4), 507–522.

OBAYORI, J. B., & UDEORAH, S. A. F. (2020). Dynamic effect of population growth on unemployment rate in Nigeria. *South Asian Journal of Development Research*, 2(3), 103-113. https://aiipub.com/journals/sajdr-200510-021041/

Omran, E. A. M., & Bilan, Y. (2021). The impact of inflation on the unemployment rate in Egypt: a VAR approach. In *SHS Web of Conferences* 107(4), 1-5. https://doi.org/10.1051/shsconf/202110706009

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics, 16*(3), 289–326. https://www.jstor.org/stable/2678547

Qureshi, M. A. (2014). ICT and unemployment in South Asia. *Journal of Economics and Sustainable Development, 5*(16), 178–190.

Romer, P. (1990). Endogenous technological change. *Journal of Political Economy, 98*(5), 71–102. https://www.jstor.org/stable/2937632

Solow, R. M. (1957). Technical change and the aggregate production function. *Review of Economics and Statistics, 39*(3), 312–320. https://doi.org/10.2307/1926047

Tsaurai, K. (2020). Macroeconomic determinants of unemployment in Africa: A panel data analysis approach. *Acta Universitatis Danubius OEonomica*, *16*(2), 89-112. https://dj.univ-danubius.ro/index.php/AUDOE/article/view/211

Zeb, N., Qiang, F., & Sharif, M. S. (2014). Foreign direct investment and unemployment reduction in Pakistan. *International Journal of Economics and Research*, *5*(2), 10-17.