

## ARTIFICIAL INTELLIGENCE AND WORKFORCE PARTICIPATION IN PAKISTAN: LINEAR AND NON-LINEAR ANALYSIS

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### Abstract

The present study analyses the influence of artificial intelligence (AI) on work force participation (WFP) in Pakistan for the period 1995 to 2024. The proxy of AI is represented through the variable of AI-related patent applications while other relevant variables involve gross domestic product (GDP) growth, gross fixed capital formation (GFCF), inflation and research & development (R&D). Impact of AI on work force participation is identified by using the Autoregressive Distributed Lag (ARDL) model. The Non-linear ARDL (NARDL) model is also adopted for analyzing the different outcomes of rises and falls in AI. The results of the ARDL as well as the NARDL methods show the impact of AI on work force participation both in the short and long term. The results also indicate that the effect of AI does not significantly differ in the case of rises and falls.

## 1. INTRODUCTION

Artificial intelligence (AI) has been a major global revolution. It is gaining widespread adoption across several sectors, and the number of businesses, public services, and other industries that have adopted this technology is growing rapidly, with a lot of applications in areas like education, healthcare, banking, agriculture, manufacturing, transport, communication, etc. Artificial intelligence enables the processing of large volumes of data, pattern recognition, predictive analytics, automation of tasks, and

making recommendations and is more likely to impact productivity, reduce costs, enhance service delivery and improve competitive position for companies (Georgieva, 2024; Gmyrek, Berg, & Bescond, 2023).

The digitalization phenomenon has led to big changes in the way companies produce goods, consume human resources, interact with consumers, and make financial decisions. Ritter and Pedersen (2020) argued that digitalization is changing business models and strengthening interaction networks between companies,

consumers, products and value chains. In this sense, AI can be considered an evolution of digitalization that makes data-driven predictions and learning and decision-making improvements. Nonetheless, the effects of AI on the labor market continue to be uncertain. There are theoretically two contradictory possible effects of AI on the relationship between AI and WFP. On one side, AI could increase WFP by generating jobs, generating a more flexible labor market, boosting digital entrepreneurship and productivity and, therefore stimulating WFP. On the other side, AI could decrease WFP by generating unemployment, skill mismatch, marginalization, and shifting from the formal to the informal sector.

AI has emerged as a fresh focus area in the National Policy for AI – National Artificial Intelligence Policy 2025 ratified by the Government of Pakistan in July 2025, which intends to promote AI innovation, develop human capital, strengthen research capabilities, and enable responsible AI deployment across sectors. The Islamabad AI Declaration 2026 also recognizes responsible AI advancement, inclusive innovation, and AI governance. However, AI implementation will require improvement in digital infrastructure, human capital development, R&D, institutional capacity, and inclusive labor-market policies.

There is only a limited amount of empirical research with respect to AI and work market participation in Pakistan. The prevailing papers tend to address information and communication technology, automation, digitalization or growth, hardly any of them with a specific focus on how AI influences labor-market activity. More than half of the working papers represent linear models with positive and negative AI change having symmetric effects, which is unlikely to be the case (Gmyrek et al., 2023).

However, the present research aims to examine the effects of AI on WFP using the most recent annual time-series data of Pakistan, 1995-2024. ARDL approach is used to determine the symmetric short-run and long-run relationships between AI and WFP. Besides, the NARDL (non-linear

ARDL) approach is used to observe the asymmetric effects of positive and negative AI shocks on WFP. The control variables such as gross fixed capital formation, GDP growth, inflation, and R&D expenditure are used in the model.

### **Organization of the Study**

Section 2 reviews the literature on the topic. Section 3 describes data and methodology. Section 4 presents the results and discussion. Section 5 presents the conclusion and provides policy suggestions.

### **2. Review of Literature**

AI is a general purpose technology that will impact production and employment in different manners. Some believe AI will improve the productivity of the workforce, lower production costs, and create demand for new jobs in digital marketing, cyber security, software development and data analysis. Others will use the technology to displace workers in routine jobs. The net effect of AI on employment will depend largely on whether the technology produces more jobs than it displaces, and whether it improves the productivity of the remaining workers.

The theoretical literature that underpins this analysis includes: neo-classical and endogenous growth theory; Schumpeterian creative destruction; and the task-based theory of technological change. In long-term productivity growth, Solow (1956) suggested technological progress is the key factor. Romer (1990) highlighted the importance of the roles of innovation, R&D, human capital and the accumulation of knowledge. Schumpeter (1942) likewise showed that innovation created new economic opportunities but also swept away old technologies and tasks. Various socio-economic constraints hinder Participation in the formal labour market (Gondal 2003; Hafeez & Ahmad 2002).

Hence, the empirical evidence on jobs and AI is mixed. Brynjolfsson and McAfee (2014) proposed that digital technologies could generate economic benefits while displacing routine jobs. Graetz and Michaels (2018) found that robot use has increased productivity and economic growth but

also decreased hours worked by low-skilled workers and reported the adverse effects of robot exposure on workers' employment and wages in the markets of robots (Acemoglu and Restrepo, 2020). Overall, existing literature leads to the conclusion that AI will probably bring about productivity growth, generate new tasks and jobs, and displace workers from a set of specific tasks, but the overall effect on human employment may hinge on the level of AI technology adoption, labor market structure, workers' skill sets, and the economy's capacity to create new jobs. Education plays a vital role to determine the market employment (Yaqoob, Hafeez, Umer, & Abubakar 2023; Ahmad & Hafeez 2007; Hafeez 2013; Ahmad & Hafeez 2016). Likewise Raza et al. (2023) and Hafeez (2015) found that investment in human beings can increase human productivity. Choi and Green Leigh (2024) argued that the adoption of AI technologies can raise the demand for workers with skills in AI but decrease the demand for some types of non-AI workers. Similarly Hwang (2024) found that the adoption of AI is associated with a larger decline in the employment-to-population ratio in U.S. commuting zones with higher levels of AI adoption, especially in manufacturing and low-skill service sectors.

The literature on AI effects on the labour market remains inconclusive. Hampole et al. (2025) suggested that the adoption of AI will make some tasks redundant but can also have a positive effect on labour demand through productivity effects in others. Wang and Wong (2025) tested the case of AI and technological unemployment. The study showed that although AI has a positive productivity effect on labour input but it may also cause displacement of workers. The ILO (2025) reported that AI is more likely to reshape and complement many occupations than to replace workers.\*

### 3. Data and Methodology

This current study is based on a quantitative time-series research method to examine the impact of artificial intelligence on workforce participation for the period from 1995 to 2024. ARDL

technique is used to determine the symmetric relationship between AI and WFP. Besides, the NARDL technique is used to observe the asymmetric effects of positive and negative AI shocks on WFP. Data sources include World Bank indicators, state bank of Pakistan etc.

### Description of Variables

#### Work Force Participation Rate (WFPR)

The percentage of the population over 15 years old who are employed or looking for work in a country. This indicator shows the percentage of human resources involved in the production process. An increase in this rate helps the GDP to grow because the more the people actively working, the more goods and services the country is able to produce. Labor force participation rate is defined as the proportion of the working-age population that is in the labor force (ILO, 2006).

#### Artificial Intelligence Patents (AI Patents)

The total number of AI patents in the economy acts as an indicator of technological innovation with regard to artificial intelligence in the country. Patents are used to protect technological innovations, which implies that much research and scientific effort has been invested in the field of AI, and that enough effort is being incentivized to develop new technologies. Countries with a greater number of patents registered in the area of AI will probably have more technological innovations in this field, which could lead to more advanced and efficient methods of production in different sectors, which could in turn lead to improvements in efficiency and economic growth. AI patents and R&D are related, and the former tend to be a result of effort put into R&D by firms and other public institutions. It is expected that there will be a positive relationship between these variables. An increase in patents will lead to a change in Workforce Participation Rate (OECD, 2018; WIPO, 2024).

#### GDP Growth

The annual rate of increase in the total value of all goods and services produced in a country compared to the previous year (World Bank, 2026).

### Gross Fixed Capital Formation (GFCF)

GFCF measures the country's rate of physical capital formation, which is important for economic growth. Having more physical capital stock enables countries to produce more output and expand their economy by contributing to higher GDP. Businesses can gain efficiencies in production through larger amounts of capital, having more machines and efficient structures (World Bank, 2026).

### Inflation Rate (INF)

Inflation, depending on the prices of the general basket of goods and services that consumers buy commonly, refers to the percentage increase or percentage decrease of these prices in the economy over a period. Inflation is usually measured by taking the Consumer Price Index (CPI). Low and stable inflation is said to be good for GDP growth

since it indicates a healthy but sustainable economy (World Bank, 2026).

### Research and Development (R&D)

Research and development refers to the total expenditure on scientific and technological development, generally indicated as a ratio of the country's gross domestic product. Following the gradual rise in R&D expenditure will help the development of production and innovation abilities, which will eventually strengthen the economy over a long time period. To emphasize the relationship between this indicator and the bank loan variables, this indicator is used as the basis for the development of the variable AI Patents, because investing in research and development provides patented ideas (OECD, 2018).

Table 1: Definition of Variables

| Variable                      | Abbreviation | Data Source   |
|-------------------------------|--------------|---------------|
| <b>Dependent variable</b>     |              |               |
| Work Force participation rate | WFPR         | WDI           |
| <b>Independent variable</b>   |              |               |
| AI Patents                    | AI_P         | OECD          |
| GDP Growth                    | GDPG         | WDI           |
| Gross fixed Capital           | GFCF         | WDI           |
| Inflation rate                | INF          | WDI           |
| Research & Development        | R&D          | WDI /Regional |

### The Model: AI and Work Force Participation

The econometric model for work force participation is specified as follows:

#### Linear ARDL Model

The long-run Labor force participation equation is specified as:

$$WFPR = F(AI\_P, GDPG, GFCF, INF, R\&D) \quad (1)$$

The general ARDL error-correction specification is expressed as:

$$\Delta WFPR_t = \lambda_0 + \lambda_1 WFPR_{t-1} + \lambda_2 AI_{t-1} + \lambda_3 GDPG_{t-1} + \lambda_4 GFCF_{t-1} + \lambda_5 INF_{t-1} + \lambda_6$$

$$R\&D_{t-1} + \sum_{i=1}^p \varphi_i \Delta WFPR_{t-i} + \sum_{j=0}^q \theta_j \Delta AI\_P_{t-j} + \sum_{k=0}^q \gamma_k \Delta GDPG_{t-k} + \sum_{l=0}^q \delta_l \Delta GFCF_{t-l} + \sum_{m=0}^q \eta_m \Delta INF_{t-m} + \sum_{r=0}^q \kappa_r \Delta R\&D_{t-r} + \varepsilon_t \quad (2)$$

where  $\Delta$  denotes the first difference, and  $t$  denotes the year. The error term is represented by  $\varepsilon$ . The lag orders are selected using an information criterion, such as the Akaike Information Criterion (AIC) or the Schwarz Bayesian Criterion (SBC). Because the sample contains only 30

annual observations, the selected ARDL model is kept relatively parsimonious.

#### NARDL Estimation Technique

To test for asymmetry, the logged artificial intelligence variable is decomposed into positive and negative partial-sum processes. Let  $\Delta AI_j$  represent the change in the logarithm of AI. The positive and negative components are defined as:

$$AI_{t+} = \sum_{j=1}^t \max(\Delta AI_j, 0) \quad (3)$$

$$AI_{t-} = \sum_{j=1}^t \min(\Delta AI_j, 0) \quad (4)$$

The positive component  $AI_{t+}$  captures cumulative increases in artificial intelligence, while the negative component  $AI_{t-}$  captures cumulative decreases. This decomposition allows the NARDL framework to distinguish whether increases and decreases in AI have different short- and long-run effects on WFP.

Nonlinear work force equation is specified as:

$$WFPR = F(AI_P, GDPG, GFCF, INF, R\&D) \quad (5)$$

This is an important correction: the positive and negative AI variables should clearly have separate coefficients,  $\beta_{4^+}$  and  $\beta_{4^-}$ .

The corresponding NARDL error-correction specification is:

$$\begin{aligned} \Delta WFPR_t = & \lambda_0 + \lambda_1 WFPR_{t-1} + \lambda_2 GDPG_{t-1} + \lambda_3 GFCF_{t-1} + \lambda_4 INF_{t-1} + \lambda_5^+ AI_{t-1}^+ + \lambda_5^- AI_{t-1}^- \\ & + \lambda_6 LRD_{t-1} + \sum_{i=1}^p \phi_i \Delta WFPR_{t-i} + \sum_{j=0}^q \gamma_j \Delta GDPG_{t-j} + \sum_{k=0}^q \delta_k \Delta GFCF_{t-k} \\ & + \sum_{l=0}^q \eta_l \Delta INF_{t-l} + \sum_{m=0}^q \theta_m^+ \Delta AI_P\{t-m\}^+ + \sum_{m=0}^q \theta_m^- \Delta AI_P\{t-m\}^- \\ & + \sum_{r=0}^q \kappa_r \Delta R\&D_{t-r} + \varepsilon_t \end{aligned} \quad (6)$$

## 4. Results and Discussion

Descriptive statistics are presented in Table 2.

Table 2: Descriptive Statistics

|              | GDPG      | WFP      | GFCF     | INF      | R&D      | AI       |
|--------------|-----------|----------|----------|----------|----------|----------|
| Mean         | 3.878573  | 48.61113 | 14.37417 | 9.403678 | 0.233332 | 9.927813 |
| Median       | 4.167185  | 50.03850 | 14.16604 | 8.492206 | 0.202795 | 9.136350 |
| Maximum      | 7.831256  | 52.73000 | 17.37707 | 30.76813 | 0.523430 | 32.26670 |
| Minimum      | -1.274087 | 43.30000 | 11.45653 | 2.529328 | 0.095360 | 0.000000 |
| Std. Dev.    | 2.101335  | 2.914225 | 1.436884 | 6.079448 | 0.109734 | 8.996806 |
| Skewness     | -0.379896 | -.583140 | 0.349320 | 1.650469 | 1.078013 | 0.468358 |
| Kurtosis     | 3.113981  | 1.859338 | 2.554870 | 6.418012 | 3.341006 | 2.335742 |
| Jarque-Bera  | 0.737843  | 3.326648 | 0.857797 | 28.22375 | 5.955912 | 1.648344 |
| Probability  | 0.691480  | 0.189508 | 0.651226 | 0.000001 | 0.050897 | 0.438598 |
| Sum          | 116.3572  | 1458.334 | 431.2252 | 282.1104 | 6.999970 | 297.8344 |
| Sum Sq. Dev. | 128.0527  | 246.2885 | 59.87442 | 1071.831 | 0.349202 | 2347.333 |
| N            | 30        | 30       | 30       | 30       | 30       | 30       |

The descriptive statistics show that GDP, AI, labour force participation, GFCF, and R&D expenditure are generally normally distributed according to the Jarque-Bera test, although their means and variations differ considerably. Inflation shows the highest volatility and is positively skewed, with the Jarque-Bera test rejecting normality. Overall, the variables exhibit different levels of variation and distributional characteristics over the 30 observations.

#### Results of Unit Root Test

After investigating the statistical properties of the baseline variables, it is crucial to determine the stationarity of the time series data to avoid spurious regression. For this purpose, the Unit Root Test is applied under different model specifications, including intercept and trend models. The empirical results of these estimations are structured and presented in Table 3 (Dickey & Fuller, 1979; Phillips & Perron, 1988).

**Table 3: Results of Unit Root Test**

| Variable Name | Model specification | t-state   | Probability | Results |
|---------------|---------------------|-----------|-------------|---------|
| GDPG          | Intercept           | -4.126216 | 0.0033      | I(0)    |
| WFPR          | Trend               | -5.925880 | 0.0000      | I(0)    |
| AI-P          | Intercept           | -6.192295 | 0.0000      | I(1)    |
| GFCF          | Intercept           | -4.704402 | 0.0008      | I(1)    |
| INF           | Intercept & Trend   | -4.342132 | 0.0117      | I(0)    |
| R&D           | Intercept           | -3.015151 | 0.0040      | I(1)    |

According to the results reported in Table 3, the variables under estimation exhibit mixed integration orders, which is a classic justification for using advanced co-integration techniques such as the Autoregressive Distributed Lag (ARDL) model. Specifically, the endogenous variable, GDP, is found to be stationary in its level form, denoted as I(0). Similarly, the work participation indicator and the inflation rate (INF) are also stationary at level, I(0). Conversely, the remaining economic determinants exhibit non-stationary behavior at their levels but become stationary after taking first differences, making them integrated of order one (I(1)). The domestic investment proxy, GFCF, becomes highly stationary at the first difference. The primary technological variable, AI, exhibits a strong structural shift towards

stationarity at the first difference. Lastly, the research and development expenditures variable (R&D Expense) confirms its I(1) integration order.

The presence of a mixed integration order, where some variables are stationary at level I(0) and others are stationary at first difference I(1), confirms that none of the series are integrated at order two, or I(2). This outcome statistically satisfies the fundamental prerequisite for conducting a long-term co-integration analysis to verify the structural relationship among the variables.

Results of bound test given in Table 4 indicate that ARDL technique can be applied to the equation of WFP.

**Table 4: Results of Bounds Test**

| Test Statistic | Value    | Significance Level | I(0) | I(1) |
|----------------|----------|--------------------|------|------|
| F-statistic    | 16.21636 | 10%                | 2.08 | 3.00 |
|                |          | 5%                 | 2.39 | 3.38 |
|                |          | 1%                 | 3.06 | 4.15 |

Results of ARDL technique is given in Table 5.

Table 5: Long Run Results for Work Force Participation

| Variable      | Coefficient  | Std. Error    | t-Statistic | Prob.  |
|---------------|--------------|---------------|-------------|--------|
| AI            | -0.002286    | 0.001571      | -1.454796   | 0.1651 |
| INF           | -0.002009    | 0.002219      | -0.905615   | 0.3786 |
| GDP           | -0.011685    | 0.028789      | -0.405892   | 0.6902 |
| GFCF          | -0.266132    | 0.185340      | -1.435910   | 0.1703 |
| GFCF(-1)      | 0.505478**   | 0.235162      | 2.149433    | 0.0472 |
| GFCF(-2)      | -0.596069**  | 0.223812      | -2.663266   | 0.0170 |
| R&D           | -0.284329*** | 0.086086      | -3.648226   | 0.0022 |
| R&D(-1)       | 0.326141***  | 0.070342      | 4.636526    | 0.0003 |
| R-squared:    | 0.695775     | D.W statistic | 1.644803    |        |
| Adj R-squared | 0.524649     | F-statistic   | 4.065852    |        |

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

The R-squared value shows that the model is explaining a large part of the variation in labour force participation. Overall, the model appears to be a reasonable explanation for the variation in labour force participation based on the economic and technology variables as it can explain, the remainder could be attributed to factors omitted from the model.

The results confirm that the impact of the regressors on labour force participation is different by both time and variables. Insignificant effect of inflation and GDP growth and AI on work force participation suggests that the estimated changes in these variables are not strong enough to justify a short-run relationship with the dependent variable using the estimated model. The effect of changing capital formation is time-dependent, contrary to the assumption that it is constant over time. The result is consistent with the ARDL, which allows the regressors to have an effect on the dependent variable in the current period, as well as through lags (Pesaran et al., 2001).

The expenditure on R&D has a significant dynamic effect on the labour force participation rate. The coefficient of current period of

expenditure on R&D is negative and the coefficient of lag expenditure on R&D expenditure is positive. It means that in the first stage expenditure on R&D reduces the participation rate and in the last stage it has a significant positive impact on labour force participation. The reason might be that the employment effects of the knowledge shocks brought about by technological and R&D expenditures may take some years to fully show up on the level of employment in the country. The result is found inconsistent with the study conducted by Uzair et al. (2024) on Pakistan, which found a positive and significant relation between expenditure on R&D and employment by using the FMOLS approach on the period 2000-2020.

GDP growth is not statistically significant but the GFCF reaches significance using the lagged values of GFCF and assumes different signs in different periods. Again, the results are inconsistent with the results of Babar and Zaman (2024), who analyzed the participation of the labour force in Pakistan with positive impact of capital and GDP. Table 6 shows the short run results of the model.

Table 6. Results of Conditional Error Correction Regression (Short-Run)

| Variable   | Coefficient  | Std. Error | t-Statistic | Prob.  |
|------------|--------------|------------|-------------|--------|
| C          | 6.989744***  | 0.812886   | 8.598673    | 0.0000 |
| WPR(-1)    | -1.507450*** | 0.145577   | -10.35499   | 0.0000 |
| AI_P       | -0.002286    | 0.001571   | -1.454796   | 0.1651 |
| INF        | -0.002009    | 0.002219   | -0.905615   | 0.3786 |
| GDPG       | -0.011685    | 0.028788   | -0.405892   | 0.6902 |
| GFCF(-1)   | -0.356724*   | 0.185937   | -1.918522   | 0.0731 |
| R&D        | 0.077812***  | 0.023668   | 3.287624    | 0.0046 |
| D(GFCF)    | -0.266132    | 0.185340   | -1.435910   | 0.1703 |
| DGFCF (-1) | 0.596069**   | 0.223812   | 2.663626    | 0.0170 |
| DR&D)      | -0.248329*** | 0.068068   | -3.648226   | 0.0022 |

Note: \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.10.

The short-run results show that labour force participation is not significantly affected by AI, inflation, or GDP growth. This indicates that these variables do not have a clear immediate effect on workforce participation in Pakistan. Recent evidence also suggests that the employment effects of technological change can differ across occupations and may involve transformation of existing jobs rather than immediate replacement (ILO, 2025).

AI has an insignificant effect on labour force participation, suggesting that the effect of AI on employment may take time to emerge. The 2025 ILO evidence indicates that AI exposure varies across occupations and that many affected jobs are more likely to be transformed than completely replaced. (ILO, 2025).

Inflation and GDP growth also show insignificant effects on labour force participation in the short run. This suggests that short-term changes in prices and economic activity do not produce a clear immediate response in workforce participation, particularly because labour-market

responses can depend on broader economic and structural conditions (Breza & Kaur, 2025).

GFCF has a negative lagged effect, suggesting that increased capital formation may initially reduce labour demand through greater use of capital and technology. However, its positive lagged change indicates that investment can also support productive capacity and employment as economic activity expands. Recent World Bank evidence emphasizes the importance of investment and capital formation for development and job creation in developing economies (World Bank, 2025).

R&D has a positive effect in one period but a negative effect through its lagged change. This suggests that research and technological investment may initially support labour demand but may later reduce demand for some tasks through technological substitution. Recent evidence emphasizes that technological change can both improve productivity and transform the tasks performed by workers (ILO, 2025).

Table 7 reveals the results of error correction model.

Table 7. Results of Error Correction Model (ECM)

| Variable   | Coefficient  | Std. Error | t-Statistic | Prob.  |
|------------|--------------|------------|-------------|--------|
| AI_P       | -0.001516    | 0.001053   | -1.439598   | 0.1693 |
| INF        | -0.001333    | 0.001482   | -0.899644   | 0.3817 |
| GDPG       | -0.007751    | 0.019158   | -0.404593   | 0.6911 |
| GFCF       | -0.236640*   | 0.123353   | -1.918399   | 0.0731 |
| R&D        | 0.051619***  | 0.015186   | 3.399180    | 0.0037 |
| C          | 4.636799***  | 0.352654   | 13.14830    | 0.0000 |
| CoinEq(-1) | -1.507450*** | 0.120661   | -12.49330   | 0.0000 |

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

The size of this co-integration coefficient is quite large, implying a swift reversion of the model to the long-run relationship in the next period. Additionally, the model performs well in providing an explanation. The high values of R-squared and adjusted R-squared show that the

variables used in the model can explain a large part of the variation in labour force participation in the short run; thus, the model provides a good explanation for the short-run factors. Results of diagnostic tests are given in Table 8.

Table 8. Diagnostic Test

| Diagnostic Test                          | Probability | Decision          | Conclusion                             |
|------------------------------------------|-------------|-------------------|----------------------------------------|
| Jarque-Bera Normality                    | 0.5861      | Fail to reject H0 | Residuals are normally distributed.    |
| Breusch-Godfrey Serial Correlation LM    | 0.0408      | Reject H0         | Serial correlation exists up to 2 lags |
| Breusch-Godfrey LM                       | 0.0130      | Reject H0         | Serial correlation exists              |
| Breusch-Pagan-Godfrey Heteroskedasticity | 0.9732      | Fail to reject H0 | No heteroskedasticity                  |
| Breusch-Pagan-Godfrey LM                 | 0.9518      | Fail to Reject H0 | Homoskedasticity                       |
| CUSUM                                    |             | Stable            | Parameters are stable                  |
| CUSUM of Squares                         |             | Stable            | Parameters are stable                  |

Results of bound test for non-linear equation are given in Table 9.

**Table 9. Results of F-Bound Test for Non-Linear Model**

| F-statistic | Significance | I(0) Bound | I(1) Bound |
|-------------|--------------|------------|------------|
| 9.962189    | 10%          | 2.334      | 3.515      |
|             | 5%           | 2.794      | 4.148      |
|             | 1%           | 3.976      | 5.691      |

**Note:** Critical bounds are based on a finite sample  $n = 30$ , which is closest to the actual sample size of 27.

Table 10 gives the results of NARDL technique with positive and negative AI effects

**Table 10. Results of NARDL Model with Positive and Negative AI Effects**

| Variable    | Coefficient | Std. Error | t-Statistic | Prob.  |
|-------------|-------------|------------|-------------|--------|
| AI_Positive | -0.001049   | 0.002408   | -0.435486   | 0.6684 |
| AI_Negative | -0.001867   | 0.003747   | -0.498304   | 0.6243 |
| INF         | -0.004815*  | 0.002835   | -1.698525   | 0.1066 |
| GDPG        | -0.012536   | 0.024496   | -1.511763   | 0.6150 |
| GFCF        | -0.072847   | 0.145438   | -0.500876   | 0.6225 |
| R&D         | 0.148680**  | 0.068971   | 2.155078    | 0.0449 |
| R&D(-1)     | 0.242812*** | 0.074103   | 3.276681    | 0.0042 |
| C           | 6.110593*** | 0.816126   | 7.487314    | 0.0000 |

**Note:** \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ .

The results show that labour force participation is not significantly affected by either positive or negative changes in AI. This means that increases or decreases in AI do not have a clear effect on the labour force in this model. Inflation, GDPG, and GFCF are also insignificant, indicating that these variables have no strong relationship with labour force participation in the estimated specification. In contrast, R&D has a positive and significant effect on labour force participation. Its positive lagged effect also shows that the impact of R&D continues into the following period. This suggests that research and innovation can create demand for skilled workers and support employment

through the development and use of new knowledge and technologies (OECD, 2026).

Overall, the asymmetric model provides no significant evidence that either positive or negative changes in AI affect work force participation. R&D, however, shows a clear positive relationship with the labour force, suggesting that research and innovation play a more important role in supporting labour-force participation in this specification. This is consistent with evidence that technological change can create new tasks and employment opportunities alongside automation (Acemoglu & Restrepo, 2019).

Table 11 presents the results of error correction estimation technique.

Table 11. Results of ECM

| Variable    | Coefficient  | Std. Error | t-Statistic | Prob.  |
|-------------|--------------|------------|-------------|--------|
| AI_Positive | -0.000713    | 0.001646   | -0.432946   | 0.6702 |
| AI_Negative | -0.001269    | 0.002563   | -0.494888   | 0.6267 |
| INF         | -0.003271    | 0.001983   | -1.649618   | 0.1164 |
| GDPG        | -0.008571    | 0.016755   | -0.511830   | 0.6174 |
| GFCF        | -0.049490    | 0.098464   | -0.502621   | 0.6213 |
| R&D         | 0.063951***  | 0.017712   | 3.610659    | 0.0020 |
| CoinEq(-1)  | -0.507450*** | 0.120661   | -2.49330    | 0.0000 |

Note: \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.10.

In conclusion, we do not find evidence that AI has a substantial asymmetric impact on the labour force participation, either in the short run or in the long run. On the other hand, R&D is positive and significantly related to the long-term labour force, implying that research and innovation seem to be more decisive factors in the effects of labour force participation in the model (Acemoglu & Restrepo, 2019; Romer, 1990).

The negative and significant error-correction coefficient confirms that the model converges towards its long-run equilibrium after experiencing a short-term shock. Additionally, the size of the adjustment coefficient, tends to show that the disequilibrium is corrected quite fast and that the variables converge to the long-run relationship in the following period (Pesaran, Shin, & Smith 2001).

Table 15. Diagnostic Test for Non-Linear Model

| Diagnostic Test                          | Probability | Decision          | Conclusion                             |
|------------------------------------------|-------------|-------------------|----------------------------------------|
| Jarque-Bera Normality                    | 0.5861      | Fail to reject H0 | Residuals are normally distributed.    |
| Breusch-Godfrey Serial Correlation LM    | 0.0408      | Reject H0         | Serial correlation exists up to 2 lags |
| Breusch-Godfrey LM                       | 0.0130      | Reject H0         | Serial correlation exists              |
| Breusch-Pagan-Godfrey Heteroskedasticity | 0.9732      | Fail to reject H0 | No heteroskedasticity                  |
| Breusch-Pagan-Godfrey LM                 | 0.9518      | Fail to reject H0 | Homoskedasticity                       |
| CUSUM                                    |             | Stable            | Parameters are stable                  |
| CUSUM of Squares                         |             | Stable            | Parameters are stable                  |

## 5. CONCLUSION

This research examined the effects of Artificial intelligence (AI) on employment in Pakistan by using time series data for the period 1995 to 2024.

The time series data covering the short and long run effects was explored through ARDL model and NARDL model to examine whether positive and negative AI have varied impacts. Our results

revealed that for neither the symmetric ARDL model nor the asymmetric NARDL model, AI was statistically significantly related to labor force participation. It inferred that in the entire observation period, AI did not have enough independent effects to have a statistically significant impact on labor force participation in Pakistan. The insignificant effect of AI does not mean that it is without relevance to Pakistan. Technology can potentially displace some jobs while simultaneously generating additional jobs and broader employment. Acemoglu and Restrepo (2018; 2019) have demonstrated that it is indeed possible that such effects are systematic. Kalai et al. (2024) found a positive effect of AI on economic growth; however the effects of AI on economic growth need not necessarily emulate the effects of AI on labor-force outcomes. Thus, the results of this study can be interpreted such that the effect of AI on the labor market may be contingent upon the structure of skills and human capital of workers, the nature of jobs and the pathways of implementation of AI across different sectors. R&D shows a more stable relationship with labour force participation. In the long run, R&D is positively significant for labour force participation in both models. This result is consistent with endogenous growth theory of Romer (1990) and the debate on social return to R&D of Jones and Williams (1998).

### Policy Implications

These results imply that the focus should not just be on the adoption of AI, but also on empowering workers to work with new technology. Spending on human capital, reskilling and technical training can help workers to move away from routine task sets towards new tasks in which technology complements and augments their work. This is especially the case for workers with poor digital skills, since they are less equipped to interact with new technologies effectively. The growing importance of reskilling is owing to the fact that technological change has the potential to not only displace jobs, but also change the composition of tasks that workers perform (Acemoglu & Restrepo, 2019).

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