THE NEXUS BETWEEN ARTIFICIAL INTELLIGENCE AND FDI IMPACT ON PAKISTAN'S JOB MARKET: NAVIGATING THROUGH SCHUMPETER AND REFUGEE EFFECTS

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Abstract
This study examines the impact of Artificial Intelligence (AI) and Foreign Direct Investment (FDI) on Pakistan's labor market. The study used Markov Switching Model to investigate the effects of AI and FDI on the labor market in Pakistan from January 2010 to December 2024. The study focuses on the dual economic perspectives of the Refugee Effect and Schumpeter's Creative Destruction, which show the contrasting effects of AI on labor markets. The findings also show that the labor force negatively affects employment in high-unemployment regimes. The research results recommend that policies, such as the government prioritizing investment in digital infrastructure, education, and workforce upskilling, be made necessary for preparing the labor markets for an AI-driven economy.

INTRODUCTION

The 21st century has witnessed AI emerge as a transformative force across global economies, reshaping human lives worldwide. It refers to the performance of machines tasks such as visual perception, problem-solving, speech recognition, and decision-making that traditionally requires human intelligence. The OECD (2023) defined AI as "the simulation of human intelligence by machines, including capabilities such as learning, reasoning, and self-correction." AI development is divided into three stages and we are surviving the third stage, known as the Machine Learning or deep learning era (Ekundayo & Ezugwu, 2025). In the context of industry, AI is also described in terms of four layers, with the fourth layer representing our current phase (Hussain & Rizwan, 2024). The development and advancements of contemporary globalization are increasingly driven by AI (Baylis et al., 2020, p. 21). Nearly every country is efforts to digitalize its economy, recognizing the transformative potential of digital technologies to foster growth, improve economic efficiency, and increase global competitiveness. Bukht & Heeks (2017) and Riley, J. (2023) defined a digital economy as economic activity driven by digital technologies such as e-commerce, cloud computing, digital services, and other internet-based platforms that drive innovation, connectivity, and economic growth. AI is transforming global economic sectors by increasing productivity, efficiency, and innovation. It is reshaping industries such as manufacturing, education, agriculture, healthcare, and retail industries. In healthcare, AI reduces costs and improves the quality of care. In agriculture, it enhances crop yield and minimizing environmental impact. AI improves manufacturing processes and transforms education by increasing the learning experiences. In retail, it enables personalization, enhances customer experience, and modernizes supply chain management. As AI continues to evolve, its influence on the global economy will intensify, presenting both significant opportunities and complex challenges for nations around the world.

AI has now shown it's possibly on a global scale. According to PwC's 2018 report, "AI is projected to add $15.7 trillion to the global GDP by 2030, representing a 14% increase in global economic output. In 2023, the global AI market was valued at $136.55 billion and is expected to rise at an annual rate of 37.3%, reaching $1.81 trillion by 2030." China, the world's second-largest economy, is leading in AI investment. It plans to invest $150 billion in AI R&D by 2030. Similarly, Pakistan though still in the early stages of AI adoption is integrating AI technologies across significant sectors such as education, agricultural, manufacturing and healthcare. The government of Pakistan has taken significant steps to boost AI. The Digital Pakistan Policy (2019) and the AI Policy (2022) aim to establish a robust digital ecosystem while promoting e-governance, youth and women empowerment, and digital literacy. These policies parallel with Pakistan's vision 2025 and vision 2035, which set determined goals to position the country the top 25 economies by 2025 and a top 10 economy by 2047. In 2021, Pakistan's IT exports reached $2.5 billion, with AI-based services contributing significantly to this growth.

AI is also reshaping job market conditions, just as it is transforming other part of economy. According to the International Labor Organization (2021), "While AI could lead to job displacement; it is also expected to create new employment opportunities. By 2027, AI could result 23% of existing jobs and 69 million new ones." In Pakistan, the tech startup ecosystem has experienced rapid growth, with over 700 st00artups emerging since 2010. Employment in the construction, storage, and communication sectors grew by 1.2% from 2014 to 2021. However, the skills gap remains a significant challenge. About 80% of IT graduates in Pakistan lack industry-relevant skills, contributing to a lack of skilled workers in the AI and broader tech sectors.

In spite of these improvements, Pakistan faces numerous challenges that could delay the realization of AI's potential. Rural areas still suffer from limited internet access. Besides, over 90% of the urban populations have access to mobile networks, penetration drops to just 40-50% in rural area. Furthermore, AI is likely to disproportionately affect low-skilled jobs, mainly in sectors such as agriculture, retail, and manufacturing. The World Economic Forum (2021) predicts that "by 2030, 1.2 million jobs will be displaced by AI in Pakistan, potentially worsening existing inequalities". Moreover, AI adoption could exacerbate gender inequalities, as women are more possible to be employed in low-wage, informal sector jobs that are at higher risk of automation.

The absence of a comprehensive data protection law in Pakistan poses significant obstacle to AI development. According to the International Telecommunication Union (ITU), "Pakistan immediately needs healthy data protection laws to safeguard privacy and increasing innovation." The cyber security risks are also on the rise, with data breaches becoming increasingly common, especially as AI systems depend on profoundly on huge amounts of data. Additionally, Pakistan's investment in AI research and development remains low compared to other countries, with the government allocating only $10 million for AI development.

Hypothesis of the study

H1: AI innovation does not significantly threaten Pakistan's job market.

H2: Labor Productivity and FDI does not contribute to job displacement or increased unemployment in Pakistan.

This study makes a significant contribution to the existing literature and addressing the research gap concerning the impact of AI and FDI on Pakistan's job market. To the best of my knowledge, no comprehensive empirical study has been conducted on the relationship between these factors in the context of Pakistan. The study is the first to examine the association between AI adoption, FDI, and the job market dynamics in the country. To explore this relationship, the study introduces new perspectives and contributes to a deeper understanding of the challenges and opportunities Pakistan faces in its digital transformation journey. As AI rapidly advances and becomes an important driver of global economic transformation, its impact on employment has become an increasing concern, mostly for third-world economies such as Pakistan. In addition, Pakistan faces the ongoing challenge of managing a growing population, which could further strain the job market. While the potential of AI to drive innovation and growth, its rapid adoption also stances the risk of technological displacement, potentially leaving many workers, especially those in low-skilled sectors, without employment opportunities.

Literature Review

AI has emerged as a transformative technology with long-lasting global implications for job markets, mostly in developing economies (Ford, 2015). Compared to previous technological revolutions, the impact of AI has been more profound, reshaping industries and workforce dynamics. Many studies have found that AI stance external challenges to job stability and threatens employee security. Studied by Rehman et al. (2017), Xie et al. (2021), Bhargava et al. (2021) and Brodowicz (2024) found that job insecurity mediates perceived threats of AI, while job dependency affected individuals' behavior outcomes within society. Concerns over job security, intense competition and limited opportunities for wage growth have been exaggerated (Zhou et al., 2020). Empirical outcomes suggested that in certain economies, AI advancements have led to wage reductions and employment shifted (Liu & Zhan, 2020). The impact of AI on job security remains a continuous issue. Nonetheless, Ojiyi et al. (2023) found that AI also has the potential to create new opportunities. Oluwaseyi and Cena (2024) suggested that AI has boosted productivity, increased the division of labor, and benefited even low-income workers by increasing efficiency and lowering prices. These AI-driven technological advancements have encouraged firms to expand production and increase demand for labor. At the same time, AI is perceived as a significant threat due to its potential to displace workers and create challenges in various sectors. Balsmeier et al. (2023) studied human-machine cooperation as a means to alleviate production constraints, increase productivity, and generate new job opportunities. In industries such as healthcare, AI has transformed roles by automating tasks like medical image analysis and chatbot-assisted diagnostics. However, automation has primarily displaced workers engaged in repetitive and manual tasks (Ojiyi et al., 2023). While AI has increased production efficiency and boosted market expansion across different skill levels (Nian et al., 2022). It has rendered certain moderated-skilled jobs obsolete (Peng et al., 2021). The Fourth Industrial Revolution has accelerated these changes, automating routine tasks and reshaping workforce skills requirements. Despite AI's potential benefits, fears of "technological unemployment" persist. The reduction in demand for human labor remained a pressing issue (Shen & Zhang, 2024). Studies by Ramos et al. (2022) and Jetha (2023) have shown that workers with lower levels education and individuals with disabilities are mainly vulnerable to displacement by automation. The growing dependence on AI has also raised ethical and policy concerns about workforce sustainability and the future of employment. The rapid advancement of AI has sparked significant discussion regarding its implication for Pakistan's job market. AI-driven automation has reshaped labor markets by displacing low-skilled workers while at the same time increasing demand for highly skilled professionals (Acemoglu & Restrepo, 2019; Haefner, Sternberg, & Weck, 2021; Lee, Wang, & Chen, 2022). This dynamic presented a considerable challenge for Pakistan, where the labor force continues to expand, yet skill development initiatives remain insufficient

(Nasir & Faraz, 2021; Khan, Ali, & Riaz, 2022). The disproportionate benefits of AI innovations for technologically advanced economies have raised concerns about job market volatility in developing nations such as Pakistan (Benzidia, Makaoui, & Bentahar, 2021; Saner, Yiu, & Nguyen, 2021; Wang, Z., Li, R., & Zhao, Q., 2023). While AI-driven technological advancements have increased productivity and economic efficiency, their benefits remained unequally distributed. The imbalance exacerbated socio-economic inequalities and limited employment opportunities for manual laborers and low-income workers (Balsalobre-Lorente, Driha, Leitão, & Murshed, 2023; Kulkov, Petrova, & Ivanov, 2023). Pakistan's manufacturing, agriculture, and customer service sectors faced potential workforce displacement from automation, necessitating targeted policy interventions (Heikkila & Xu, 2022; Petrescu et al., 2022; Truong & Papagiannidis, 2022). Nonetheless, AI also offered opportunities for economic transformation by fostering new job roles and enhanced labor market efficiency (Leimanis & Palkova, 2021; Vinuesa et al., 2020). Furthermore, reskilling initiatives and strategic investments in AI adoption were considered essential for mitigating potential job losses and ensuring Pakistan's workforce remained competitive (Truby, 2020). The association between AI adoption, workforce transformation, and economic inequality, there was an urgent need for a balanced policy framework that integrates AI-driven progress with sustainable employment strategies (Wang, T., & Ma, H., 2024). The existing literature suggests that while AI stance significant challenges to Pakistan's labor market, its overall impact depends on the country's ability to adapt through proactive education and workforce development policies (Abulibdeh et al., 2024; Wang, Y., Li, & Zhang, 2024). Thus, the hypothesis that AI innovation did not significantly threaten Pakistan's job market remained a subject of empirical investigation, with outcomes contingent upon the effectiveness of policy responses and adaptive labor market strategies (Voumik, Shah, & Rahman, 2023; Muhammad et al., 2025).

H_0: AI innovation does not significantly threaten Pakistan's job market.

AI's global integration reshaped labor markets, causing widespread job displacement and unemployment. Population growth significantly affected the labor market, particularly in unskilled sectors. AI-driven technologies boosted productivity and effectiveness; however, it unclear whether they caused widespread job losses or merely reshaped employment patterns by a shifting demand toward add additional skill sets (Haefner et al., 2021; Lee et al., 2022). Acemoglu and Restrepo (2019) examined that automation displaced labor in some sectors but simultaneously created new tasks, leading to job restoration. Bessen (2019) studied that AI-driven technological advancements did not necessarily decrease employment but instead shifted labor demand across sectors. In contrast, Frey and Osborne (2017) estimated that about 47% of jobs in developed economies were at risk due to automation, raising concerns about its implications for developing countries such as Pakistan.

The World Economic Forum (2020) provided a more balanced perspective, predicting that AI would generate 58 million new jobs across the globe in 2022. It indicated that technological disruption was not purely negative (Chowdhry, 2018). AI adoption in developing countries presented select challenges because of lower adaptability and weaker labor market structures. Bain (2016) and Yusuf (2017) found that AI-driven automation posed a substantial threat in these regions, as industries were often unable to transition workers into new roles. Li et al. (2023) and Kalhor and Emaminejad (2019) emphasized the role of urbanization in shaping employment dynamics, proposing that AI-driven technological transformation influenced employment sustainability, mainly in relation to disparities between rural and urban labor markets. These challenges highlighted the need for strategic workforce development to mitigate job displacement risks. In Pakistan, structural risks in the labor market amplified the effects of automation. Rehman et al. (2017) showed significant vulnerabilities that hindered workforce adaptableness, making AI-induced labor shifts more disruptive. Rapid population growth further intensified job demand. While automation contributed to job displacement, it also created new employment opportunities, with outcomes depending on economic policies and labor market adaptability.

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In developing economies like Pakistan, where workforce transition mechanisms remained weak, the risks associated with AI-driven automation appeared more pronounced. Ultimately, the extent to which AI disrupted or enhanced employment depended on strategic policy interventions and investment in skill development to ensure a balanced transition in the labor market.

H_0: Labor Productivity and FDI *does not contribute to job displacement or increased unemployment in Pakistan.*

In conclusion, AI redefined the job market, presenting both opportunities and challenges. While it enhanced productivity and created new employment prospects, it also intensified job insecurity and labor displacement. Future research and policy interventions were required to address these dual effects, ensuring a balanced and inclusive workforce transition in the AI-driven era.

METHODLOGY

Data and Methodology

This study used monthly data over period January 2010 to December 2024. The eight variables divided into output (Unemployment rate) and input (Independent variables). The input variables further separate into focused variables artificial intelligence (AI), big data (BD), data science (DS) and Machine learning (ML), functional variables Global trend Index (GTI), productivity of labor (POL) and foreign direct investment (FDI), and control variables labor force (LF). Currently various studies used this variable such as

Variables	Abbs.	Sources	Sources
Unemployment rate	UNER		Nguyen & Vo, (2022), Guliyev, (2023), Mutascu, (2021), Qin et al., (2024), Guliyev et al., (2023), Abid et al., (2024), Simionescu & Cifuentes-Faura, (2022), Masoud, (2025)
artificial intelligence	AI	Google Trend Singapore (GTS)	Masoud, (2025), Qin et al., (2024), Guliyev, (2023), Mutascu, (2021) and Guliyev et al., (2023).
Big Data	BD	(GTS)	Masoud, (2025), Abid et al., (2024), Guliyev et al., (2023), Guliyev, (2023), Simionescu & Cifuentes-Faura, (2022)
Data Science	DS	(GTS)	
Machine Learning	ML	(GTS)	
Global Trend Index	GTI	(GTS)	
Labor Force	LF	IMF	
Productivity of Labor	POL	ILO	Abid et al., (2024), Mutascu, (2021), Masoud, (2025), Nguyen & Vo, (2022), and Guliyev et al., (2023)
Foreign Direct Investment	FDI	WDI	Mutascu, (2021), Guliyev et al., (2023), Abid et al., (2024).

Model Specification

Keeping in view the main objective of the current study and the nature of the variables, we specified the functional forms and their model formulation below. The general models as follows:

$$Y = \sum_{i=1}^{n} X_{it} + u_t \dots (1)$$

Now

$$UNEMPLOYMENT_t = Intercept + \sum_{i=8}^{8} \beta_8 X_8 + \varepsilon_{it} \dots (2)$$

Y is the Response variable (e.g., Unemployment rate)

X1, X2... X_n are the Input Variables of the specific model.

$\sum_{i=1}^{n} X_{it}$ Indicates the sum of the Input Variables of the model.
ε is the error term, i and t shows obs. and times respectively.
Now, write the *econometric model:*

$$UNEMP_t = \beta_0 + \beta_1 AI_i + \beta_2 BS_t + \beta_3 DS_t + \beta_4 MAL_t + \beta_5 GTI_i + \beta_6 LNLF_t + \beta_7 POLG_t + \beta_8 FDI_t + \varepsilon_t \dots (3)$$

Where;
$B_1<0$, $\beta_2>0$, $\beta_3<0$, $\beta_4>0$, $B_1<0$, $\beta_2>0$, $\beta_3<0$, $\beta_4>0$
The sign > indicate positive association and < indicates negative association.
t=1, 2, 3 …. T

Theoretical Framework

Technological advancements, mainly AI and automation, are reshaping labor markets worldwide, with significantly effecting the developing economies such as Pakistan. The country faces the dual challenges of a high population and limited AI awareness, leading to concerns about mass unemployment economic displacement and job polarization. The Joseph Schumpeter's theory of technological displacements shows the concept of 'Creative Destruction." (Abdesselam et a., 2014). Where technological progress, particularly, AI, displaces workers in traditional industries reliant ton low-skilled, and routine jobs. Through AI eradicates old positions, it also generates new economic opportunities through entrepreneurship and innovations (Newman et al., 2024). The growing impact of AI across various sectors in Pakistan creates both challenges and potential for economic growth, which must be addressed through active policies and investments in skills development and education. AI's probable to displace jobs is mainly obvious in sectors such as serving, agricultural, manufacturing, customer service, and retail, where automation replaces routine tasks. The worsen structural unemployment and enlarge economic inequality, as several workers lack the skills required to transitions to new roles. However, AI also has the possible to create new jobs in emerging industries such as IT, automation, data science, cybersecurity, digital finance, and etc. To benefit from on these opportunities, Pakistan must emphasize on investing in workface upskilling, AI's education and policies that increase innovation. The effect of AI-induced displacement and job creations can be investigated through two economic perspectives: the 'Schumpeter Effect' and 'Refugee Effect'. The Schumpeter Effect focus on the process of 'Create Destruction," wherein technological advancements particularly automation and AI can lead to the displacement of workers, mainly in industries that depends on low-skilled and routine jobs (Boianovsky & Trautwein, 2010; Abdesselam et a., 2014; Huggins & Thompson, 2015; Newman et al., 2024; Emami Langroodi, 2021). Besides, The Refugee effect proposes that AI-driven job losses could exceed job creation if workers are unable to transition the new roles particular in those economies where weak labor market structures. In Pakistan, the refugee effect could worsen social instability and economic inequality if adequate steps are not taken to reskill the workforce and implement AI infrastructure (Abdesselam et a., 2014; Aubry et al., 2015; Huggins & Thompson, 2015; Emami Langroodi, 2021).

Now, these challenges and opportunities will be critical to shaping its future. To provide AI education, workforce upskilling, and investment in AI-driven industries, Pakistan can certify that job creation keeps pace with automation. Furthermore, confirming reasonable access to AI opportunities, mainly for rural populations, is essential for lessening the risks of technological unemployment. Thus, the Pakistan's labor market depends on its ability to integrate AI into its economic framework. If the country raises innovation, adapts its workforce, and implements complete digital policies, it can connect AI to drive economic growth while diminishing the negative effects of job displacement. The decisions made today regarding AI policy, education, and workforce development will determine whether Pakistan thrives in the AI-driven economy or faces the challenges of technological disruption.

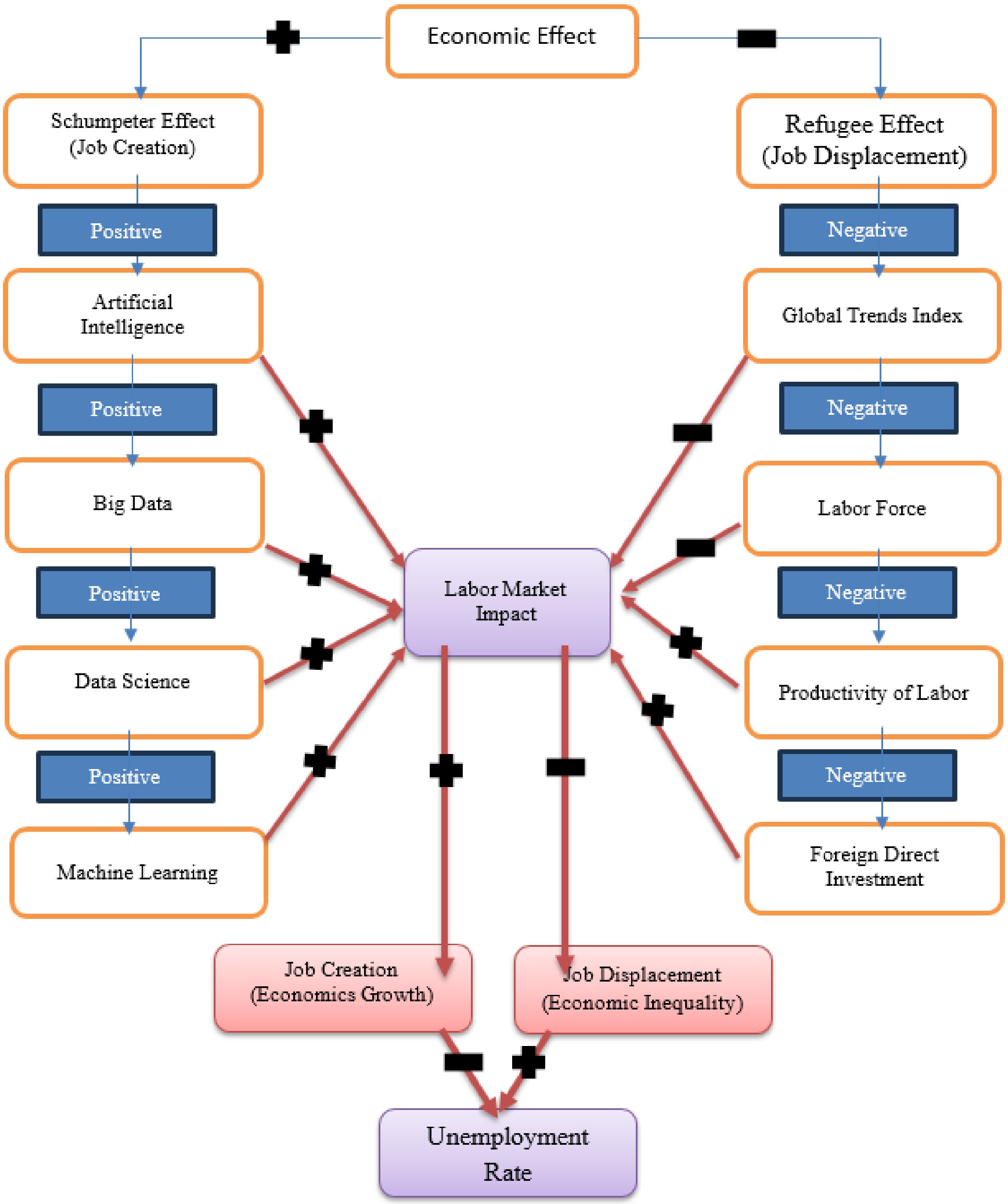


Figure 1: Theorettical Fromwork

UNIT ROOT TEST

To obtain reliable and valid estimates of the parameters in time series data, checking the stationarity of the variables is a prime step. Ignoring the stationarity issue, the obtained results can be spurious, and inferences made on such estimated results would be misleading. Therefore, we have checked all the variables for being stationary and non-stationary. A series is said to be stationary if its mean, variance, and covariance are time-independent; otherwise, it is non-stationary. Various tests are available in the literature to test a data series for stationary or non-stationary, such as Dickey and Fuller (DF), Augmented DF (ADF), and PP tests. In the current study, we have used the ADF test introduced by Dickey-Fuller (1984) and the Phillips-Perron unit root test developed by Phillips and Perron (1988). To determine stationarity, the criteria for evaluation were as follows: if the absolute value of the t-statistics exceeded the absolute critical value defined by MacKinnon (1999), the variable in question was deemed stationary. Similarly, if the p-value associated with the t-statistic was less than 0.05 (considering a 95% confidence interval), it indicated the rejection of the null hypothesis in favor of the alternative hypothesis (Ullah et al., 2023). In other words, our variable is stationary. ADF and PP are tested by changing the stationary value of a variable. If a variable turns stationary at a level, it is represented as I (0). Otherwise, it is represented by I (1) and I (2), first order and 2nd order stationary, respectively. Once all the variables are tested for this issue, the specified models are estimated using appropriate regression techniques (Gul et al., 2023; Rehman et al., 2023; Ikram & Gul, 2024).

Regime Switching Model

This study used the Markov-Regime-Switching (MS) model. Through this methodology examine the impact of Artificial intelligence (GIT[1]) on unemployment rate along with focused, functional and control variables such as *AI, BD, DS and BS, GTI, POL, FDI and LF respectively. The specific purpose for using the MS model was shift the AI policies in the late 2000s in Pakistan. To investigate the association between the AI and unemployment, we measure the two-state MS model (MS-2) following Rahman et al., (2020). Thus, we consider the Means (μ_{st}), variance (σ_{st}) and artificial intelligence (Global Trend Index, GTI_{st}) while, artificial intelligence, (AI), big data (BD), data science (DS) and labor force (LF), productivity of labor (Pol) and foreign direct investment (FDI) remain are non-switching variables.*

2.5. Markov regime-switching (MRS-Method)

It is used in the term series and assumed to be stationary and influenced by a latent process. Thus, states (St, t=0,1) remain unobservable which evolves in time series. The model assumed that significant parameters such as $\mu(_{st\ where\ t=0,1})$, $\sigma(_{st\ where\ t=0,1})$ *and Global Trends Index coefficient* $GTI_{(st\ where\ t=0,1}$) *are regime dependent.* This means that the parameters (of the Means, variance and dependent variables) are measure about the regimes. The model considers two separate regimes: regime 0, which related with high average unemployment rate, while regime 1 is associated with low unemployment rate. Thus, $\mu0 > \mu1$ and $\sigma0 < \sigma1$ showing a high-unemployment, High-GTI (AI Technology) vice versa. The MS model can be written as:

$$\Delta Yt = \mu_{st} + \beta_{st}\delta_t + \sum_{i=1}^{8} \gamma_i \Delta X_{it} + \varepsilon_{st} \dots . (4)$$

In Equ. (4), ΔYt refers the change in unemployment rate, μ_{st} is intercept of the state of dependent, δ_t shows state-dependent of the switching variable, that is $UNEMP_t$ and ΔX_{it} are state of the explanatory Variable such as $\Delta AI_i, \Delta BS_t, \Delta DS_t, \Delta MAL_t, \Delta GTI_i, \Delta LNLF_t, \Delta POLG_t,$ and ΔFDI_t, whereas $\varepsilon_{st} \sim$ i.i.d. N(0, σ^2). Now probabilities:

[1] The Global Trends Index is a composite index designed through Principal Component Analysis (PCA) of four significant components: Artificial Intelligence, Data Science, Big Data and Machine Learning. Thus, Artificial intelligence is considered in its abroad sense.

$$st = \begin{cases} 0, \; probability \; is \; P_{00} \\ 1, \; probability \; is \; P_{00} \end{cases} \quad \ldots (5)$$

and

$$P_r = \begin{vmatrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{vmatrix} \text{ and } \sum_{j=1}^{m} P_{ij} = 1 \; for \; i = 0 \; and \; i = 1 \ldots (6)$$

In Equ. 6 the P_{00} and $P_{11}$are indicating the remaining probability of the regime 0 and 1 respectively. Besides, the $P_{01}$and P_{10} showing the probability's movement from 1 regime to another. Therefore, the rows (P_{00} P_{01} & P_{10} P_{11}) refers the current state while column (P_{00} P_{10} & $P_{01}P_{11}$) representing the next state. Each element P_{ij} represents the probability of transitioning from state I to state j, as well as the sum of each row is 1 which is confirming this is a valid Markov transition matrix. Now

$$P_{ij} = pr(st = j | st - 1 = i) \forall \; i, j = 0\&1 \ldots (7)$$

In MS (2) model, μ_{st} *and* σ_{st} *are predictable to perform as:*

$$\mu_{st} = \begin{cases} \mu_0 \\ \mu_1 \end{cases} > 0 \; \& \; \mu 0 > \mu 1 \text{ and } \sigma 0 < \sigma 1 \ldots (8)$$

Thus, 0, which related with high average unemployment rate, while 1 is associated with low unemployment rate. Now, Equ. (7) and (8) are created by ergodic probability which are given in equations (9) to (12).

$$P_{00} = pr(st = High \; Unemployment \; rate \; regime \; | st - 1 = HIgh \; Unemployment \; rate \; gegime) \ldots (9)$$

$$P_{01} = pr(st = High \; Unemployment \; rate \; regime \; | st - 1 = Low \; Unemployment \; rate \; gegime) \ldots (10)$$

$$P_{11} = pr(st = Low \; Unemployment \; rate \; regime \; | st - 1 = Low \; Unemployment \; rate \; gegime) \ldots (11)$$

$$P_{10} = pr(st = Low \; Unemployment \; rate \; regime \; | st - 1 = High \; Unemployment \; rate \; gegime) \ldots (12)$$

We used over 1,000 initial values for the estimated specification to improve parameters worldwide. In addition, we considered the maximum log-likelihood ratio (LR) test, residual analysis, and the Regime Classification Measure (RCM) to identify the optimal model (*Rahman* et al., 2020; Charfeddine & Goaied, 2019).

Diagnostic Tests

The diagnostic tests determine the validity and reliability of a model. The primary goal of diagnostic testing is to evaluate whether the basic assumptions of the regression model are met and to identify any potential problems that might distort the results. If any assumptions are violated, the model's conclusions may be misleading or incorrect. There are many benefits to using these diagnostic tests, such as detecting problems and ensuring that the model is valid. With diagnostic testing, conclusions drawn from a regression model may be correct, leading to better decision-making based on accurate or misleading results.

Table 1 descriptive statistics

	UNEMP	AI	BD	DS	ML	GTI	FDI	LF	POL
Mean	6.049	12.66	29.41	29.63	35.26	0.879	0.607	5.75	8.203
Median	6.04	4.0	31.0	17.5	2.5	0.880	0.575	5.38	8.322
Maximum	6.91	100.0	100.0	100.0	100.0	2.325	1.027	56.09	9.290
Minimum	4.96	1.0	0.0	0.0	0.0	0.020	0.343	52.50	6.673
Std. Dev.	0.454^{L}	22.03^{H}	17.71^{H}	30.25^{H}	31.14^{H}	0.470^{L}	0.171^{L}	1.148^{M}	0.826^{L}
Skewness	-0.566^{-LS}	2.519^{+RS}	0.475^{+RS}	0.696^{+RS}	0.582^{+RS}	0.759^{+RS}	0.675^{+RS}	0.844^{+RS}	-0.303^{S}
Kurtosis	3.361^{L}	8.008^{L}	3.896^{L}	2.113^{P}	1.896^{P}	3.953^{L}	3.273^{L}	2.344^{P}	1.715^{P}
Obs.	180	180	180	180	180	180	180	180	180

This table shows the described statistics. L, M, and H referring Low (<0.5), Moderate (0.5-1.0), and high (>1.0) variability in specific datasets. The -LS and +RS show the negative (Left-skewed) and positive (Right) Skewness, respectively. Besides, the zero value of the Skewness shows the perfectly symmetrical). Therefore, kurtosis value range 3 (>3 shows or Leptokurtic and <3 describes the - or Platykurtic) and =3 shows normal (Mesokurtic).

Table 1 describes the results of the specific dataset. The mean value of unemployment is 6.049, and relatively stable with low variation. It is negatively skewed (Mean < median or low outliers) and leptokurtic. AI, DS, and ML show extreme right-skewed (Means > median or high outliers) and high dispersion (Std. Dev. > 20, it is more unpredictable), presenting concern for low values with few high outliers (e.g., max=100). Therefore, POL shows low variability (Small Std. Dev) and near-symmetric distribution (mean ≈ median), which suggests stable trends compared to GTI and FDI. The GTI and FDI also show a low variability (Std. Dev. is 0.47 and 0.17, respectively) while right-skewed (Means > Median, or high outliers). The POL and LF have low variation, with POL slightly left-skewed (Mean < Median), which means stability is commonly high. The BD has a moderate variation with a near-normal distribution. Thus, the specific data suggests a significant variation in technology adoption (AI/DS/ML) compared to more consistently distributed economic variables such as unemployment rate and FDI). Similarly, the analysis addresses outliers and transformations for skewed variables (Gul & Khan, 2021; Khan et al., 2023; Gul et al., 2023).

Table 2 Correlation

	UNEMP	BD	AI	DS	ML	LF	FDI	POL	GTI
UNEMP	1								
BD	-0.2408	1							
AI	-0.3175	0.0532	1						
DS	-02895	0.5533	0.6882	1					
ML	-0.1362	0.6270	0.6548	0.7981	1				
LF	-0.3189	0.2710	0.7379	0.8064	0.7724	1			
FDI	-0.4224	-0.072	0.3123	-0.307	0.3087	0.3604	1		
POL	-0.2245	0.5899	0.5080	0.7827	0.7356	0.7899	0.3616	1	
GTI	-0.3129	0.5398	0.6846	0.8026	0.7684	0.8064	-0.3101	0.7962	1

Table 2 describes the correlation results (Figure 2 also interprets this outcome). There are two primary purposes of correlation: first, to find the association between variables, and second, to detect multicollinearity. Multicollinearity issues exist if the association between the input variables exceeds 0.8 (Kennedy, 2008; Gujarati & Porter, 2009; Wooldridge, 2016). The correlation analysis in Table 2 shows that Pakistan's unemployment is negatively associated with all significant policy and technological indicators, such as AI, BD, ML, DS, LF, and GTI. The negative association, especially with AI (-0.3175), GTI (-0.3129), and FDI (-0.4224), suggests that sympathetic government policies and technological advancements are contributing to a decline in unemployment. This trend replicates the Schumpeter Effect, where innovation shoots new economic activities, increases productivity, and creates new employment opportunities. In developing countries like Pakistan, where the population is rapidly growing, and unemployment is a pressing concern, the positive association between job reduction implies a transformative role for technology in reshaping the labor market. Thus, not all association indicators smooth technological integration. Thus, the mixed association involving FDI is positive with AI but negative with GTI and DS, highlighting possible mismatches between investment trends and innovation sectors. This misalignment may show transitional resistance within the economy, where specific sectors are interested in investment. In contrast, others lag, and these patterns are associated with the refugee effect, which explains the displacement of workers during structural shifts. In Pakistan, where much of the labor force remains semi-skilled (or informally) employed, the return of AI and automation can temporarily displace workers who are unprepared for tech-driven roles, worsening inequality if not managed through upskilling initiatives. Despite these challenges, the strong positive association among LF, DS, ML, and GTI may exceed 0.7, showing growing cooperation between workforce engagement and technological adoption. Pakistan's supportive ecosystem, fueled by policy reforms and digital investment, boosts labor market engagement in its innovation economy. Ultimately, crossing this nexus between population growth and AI's impact demands that Pakistan strategically balance the Schumpeter promise of innovation-led growth with safeguards against the Refugee effect's social fallout. The proper econometric approach, such as the Markov-Switching model, is necessary to conflict the direction and effect.

Table 3 BDS test Results

Dimension	BDS Statistic	Std. Error	*z*-Statistic	Prob.
2	0.024914	0.006468	3.851769	0.0001*
3	0.050109	0.010321	4.855021	0.0*
4	0.066567	0.01234	5.394198	0.0*
5	0.071313	0.012915	5.521673	0.0*
6	0.067664	0.012506	5.410347	0.0*
**H_0: *The Residuals are independently and identically distributed (iid) [or Series are linearly dependent]*				

* and **it indicates that the significant at 1%. It means that the series have no serial dependence, no stochastic structure (deterministic) and it purely random with no hidden patterns.

A linear time series model represents the present value as a linear function of past values and a random error term (or residuals). A significant characteristic of a linear model is that the residuals should be independent and identically distributed (iid) after fitting the model, meaning no further patterns or dependence should remain in the residuals (to estimate the past value and random noise, any residual values should not show systematic relationship). The Brock-Dechert-Scheinkman (BDS) test ((Brock et al. 1996) is a non-parametric approach used to detect non-linearity in the time series data and test whether it is iid. The BDS results show that the probability value of the *z*-statistics under all dimensions is less than 0.01, which means rejecting the null hypothesis of iid at a 1% significant level. This reliable rejection across dimensions offers robust evidence that the time series contains non-linear dependencies. In applied econometric terms, the residuals have structure after linear filtering, and the linear models poorly describe the data's behavior entirely. These findings justify using non-linear models, such as regime-switching models, for a more accurate analysis of the fundamental AI dynamics. In table 4 shows the results of unit root tests (ADF and PP) on the estimated variables. It shows their order of integration. Most variables, such as AI, BD, GTI, ML, and LF, are integrated in order 1, meaning they are non-integrated at the level but become integrated at the first difference. Besides, DS and UNEMP are exceptions, with UNEMP possibly revealing mixed results and DS showing integration in the PP test. Besides, The FDI and POL are integrated at each level. So, overall results show that all variables are stationary in mixed order.

Table 4 Unit ROOT TEST

Variable	ADF				PP				Decision	
	I(0)		I(1)		I(0)		I(1)			
	constant*	I&T**	constant*	I&T**	constant*	I&T**	constant*	I&T**		
	T-test	T-test	T-test	T-test	T-test	T-test	T-test	T-test		
UNEMP	-11.34	-11.30	-	-	-11.42	-11.38	-	-	I(0)	Mixed order of cointegrated
BD	-2.07	-2.22	-11.87	-11.89	-2.76	-3.77	-	-	I(1)	
AI	2.68	2.05	-1.77	-3.94	4.10	2.81	-8.87	-9.45	I(1)	

DS	0.95	-3.52	-	-	-0.52	-3.14	-20.23	-24.35	I(0)
ML	-0.29	-2.89	-19.74	-19.72	-0.16	-3.65			I(1)
GTI	-2.45	-2.75	-10.59	-10.63	-2.13	-2.45	18.19	-21.01	I(1)
LF	-1.59	-2.89	-7.56	-7.66	-1.21	-2.68	-14.93	-15.16	I(1)
FDI	-4.17	-11.30	-	-	-4.29	-4.42	-	-	I(0)
POL	-2.03	-3.29	-13.36	-13.32	-2.11	-3.66	-	-	I(1)

* and ** indicate the critical value -2.87 and -3.43

Table 5 Residual analysis of linear and MS models

statistics		Linear Model	MS Model
Panel-a			
Descriptive statistics	Means	-1.645e+15	0.004748
	Std. Dev	0.550335	0.485328
	Skewness	-0.576417	-0.601060
	Kurtosis	3.283567	3.775432
Panel-b			
Diagnostic statistics	Log-likelihood	102.3451	121.8041
	LR-Linearity test	-	23.432 [0,0000] **
	Approximate upper bound		0.0001 **
	Jarque-Bera	0.5166	0.815
	ARCH 1-1 Test	0.2154	0.892
	Q (12)	3.6132 [0.9323]	2.5124[0.5319]
	Q^2 (12)	6.4649 [0.4955]	3.2052 [0.2178]
	RCM	-	1.8635
Panel-c			
Criterion Information	AIC	-5.3432	-5.6429
	HQ	-5.9631	-6.1460
	SC	-6.0343	-6.3415

The impact of AI and FDI on Pakistan's labor market was investigated using Markov Switching farmwork. Because of the small sample, our analysis only used two regimes. The diagnostic tests confirm the robustness of the Markov Switching model and confirm that no autocorrelation and residuals are normally distributed. The descriptive stats part shows that the MS model is more sensitive to the effects of regimes than a linear model. The standard deviation of the MS model predicts stable unemployment behavior as it swings between two economic conditions. All three model selection criteria chose the Markov Switching (MS) model over the simple linear model by having low AIC in the MS model, and the HQ confirms the goodness of fit in the MS model. Therefore, the linear model failed to estimate the structural shifts in the job market due to varying macroeconomic conditions, qualifying the uses of the MS (2) framework. Now, it describes the outcomes of the linear and MS models. The MS model defines two separate regimes: Regime 1 is associated with higher unemployment and volatility.

Table 6 Estimates of linear and MS model (January 2010 to December 2024)

Variable	UNEMP	
	Linear Model	MS Model
Mean(μ_0)	0.047***(0.053)	0.084***(0.0045)
Mean(μ_1)		0.058***(0.0028)
Variance (σ_0^2)	0.1086**	0.07712***

Variance (σ_1^2)		0.0816***
GTI_0	0.2259** (0.067)	0.5244*** (0.1355)
GTI_1	-0.00425*** (0.00244)	0.3138***(0.0168)
AI	0.00164(0.0183)	0.4454*(0.0642)
BD	0.00545 (0.00374)	0.0287(0.3168)
DS	-0.548 (0.368)	0.00581(0.00623)
ML	0.00837 (0.00821)	0.00669(0.00445)
ΔLF	-0.0422*** (0.0227)	-0.252**(0.120)
FDI	0.899*(0.154)	0.3133 *(0.178)
POL	0.652*(0.0861)	0.5780***(0.229)
Probabilities matrix	-	$\begin{bmatrix} 0.7880 & 0.2110 \\ 0.3710 & 0.6290 \end{bmatrix}$

The presence of AI does not significantly reduce joblessness. It's disruptive, possibly because of the Schumpeter effect. The effect suggests that technological progress, particularly AI and automation, leads to innovative destruction where traditional jobs are displaced earlier than new ones. *This regime's high variance ($\sigma_1{}^2$ = 0.0816) and instability mirror the labor market's difficulty integrating displaced workers, especially without sufficient institutional or educational backing.* In regime 0, the ΔLF coefficient is negative (-0.252**), so low FDI and low and low productivity increase the risk. The inability to create enough tech-compatible jobs worsens unemployment. Besides, regime 0 suggests low unemployment and economic stability and supports the Refugee effect. The effect shows that AI integration leads to job creation or reallocation of labor. The positive and significant AI suggests that when macroeconomic conditions are stable, AI acts as a productivity increase and job stimulator, not a job destroyer. This could be due to harmonizing effects, where AI enhances various sectors, such as e-commerce, finance, and digital services, creating new jobs and absorbing displaced labor. The positive and significant impact of GTI0 and FDI in this regime further supports innovations. It can help unemployment if supported by foreign capital and global tech flows. AI is substantial in the MS model, which reveals the difference in economic regimes. BD, DS, and ML have no statistically significant effect on unemployment in Pakistan. The labor force positively and significantly affects unemployment in the linear model. Still, it has a negative and significant effect in the MS model, suggesting the difference in impact on unemployment in both models. The results also show that the labor force negatively affects employment in high-unemployment regimes. It shows that a high labor force exacerbates joblessness during economically stagnant periods because of limited absorption capacity and skill mismatches. It is a common issue in labor-surplus economies such as Pakistan. These factors, such as POL, FDI, and GTI, consistently show strong positive effects on employment across regimes and emphasize their role in imitating the possibility of AI.

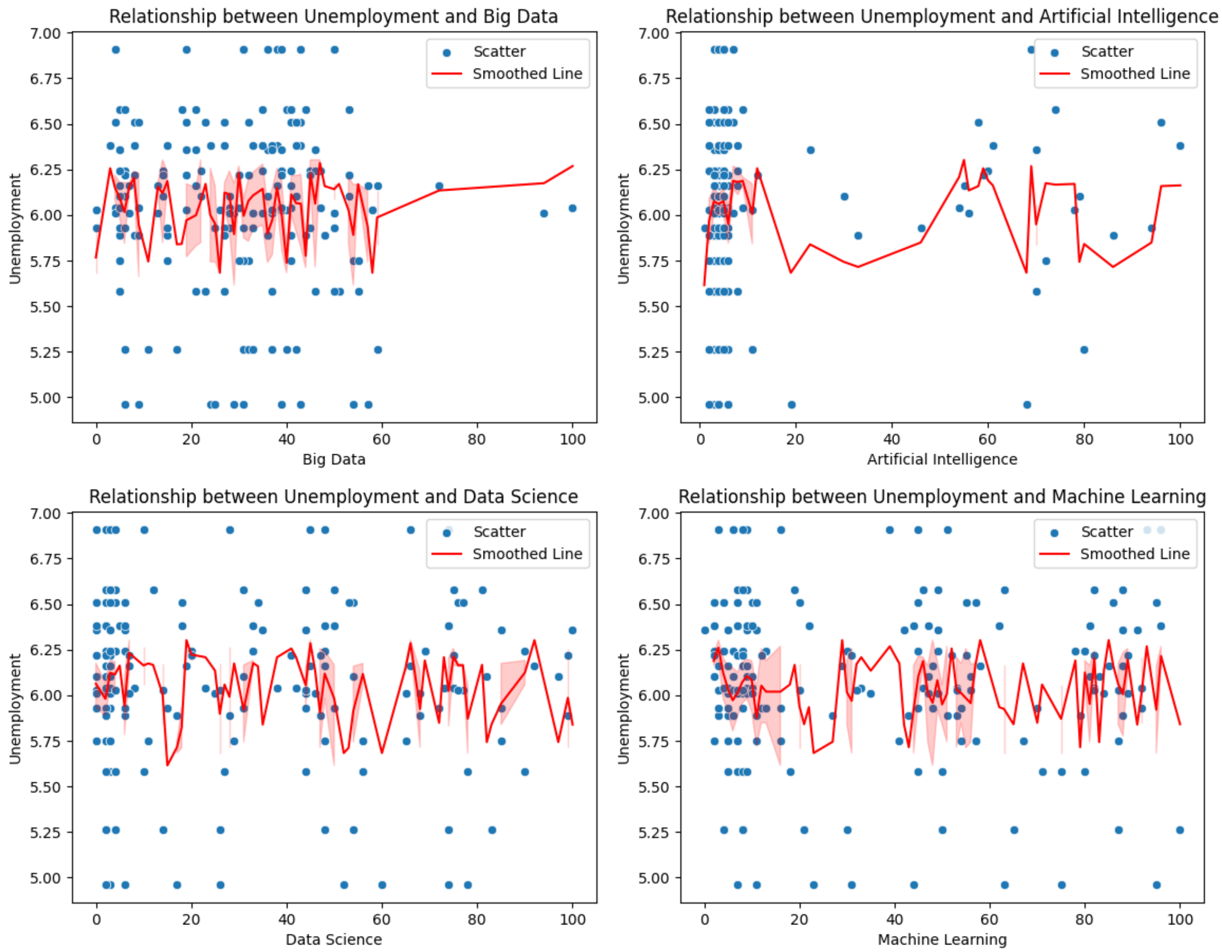
In conclusion, the factors need targeted policy interventions that improve labor market flexibility, increase workforce skills in line with technological advancements, and promote political and economic stability. Supporting AI adoption in a controlled and inclusive manner can help Pakistan move from a displacement-prone regime to a tech-driven, employment-expanding regime. Policymakers need to understand that merely adopting new technologies is not a solution. Therefore, whether AI becomes a threat or a tool for inclusive job growth depends on its empowering environment.

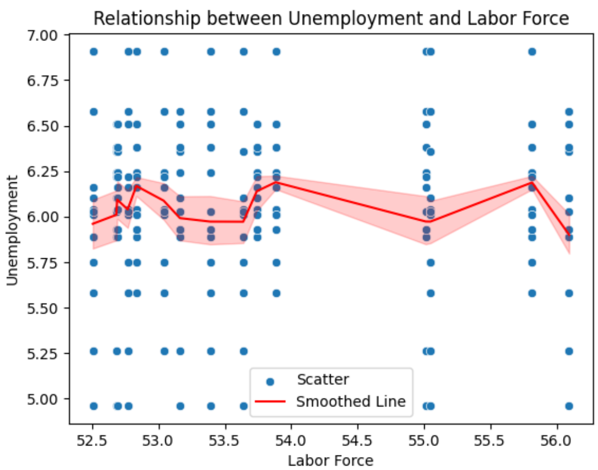
Table 7 Regime classification of MS base on duration

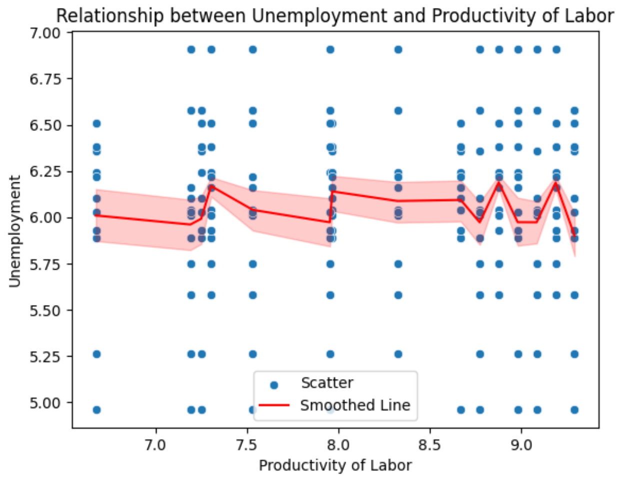
	High Unemployment	Low Unemployment
Months	39 months	141 months
In % term	21.62%	78.39%

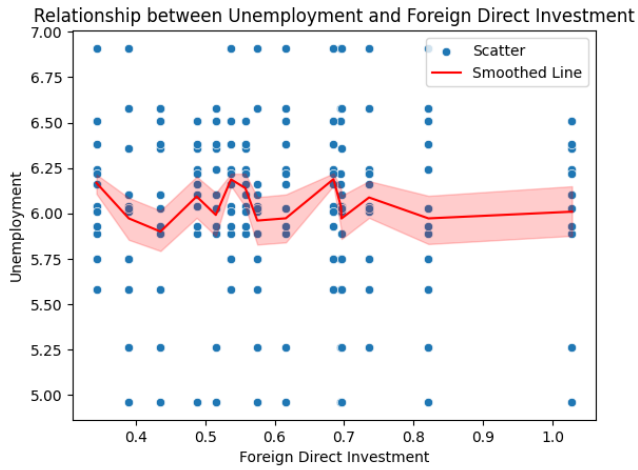
Average duration	16 months (1.33 years)	50 months (4.14 years)
Steady-state probabilities	20.90%	79.10%

Table 7 presents the Switching of the Markov model for high and low unemployment regimes. The model was about the distinct economic conditions and how long the economy stayed in each regime. It shows that the economy spent 21% of its total time in a higher unemployment regime during 141 months, i.e., 78% of the time in a low unemployment regime. The higher unemployment regime is short and implies a temporary shock. The steady-state probabilities confirm that the economy is in a low unemployment state in the long run compared to a high unemployment state.









There is a non-linear relationship between big data and unemployment. The relationship is weak despite the upward trend at higher values of Big Data. The second plot shows the relationship between unemployment and AI. The clustered data points show low activity on AI most of the time. Adopting AI during the mid-period is associated with a slight decline in unemployment, apparently because of technology-driven opportunities. However, higher levels of AI show an increase in unemployment. The response of Data Science to unemployment is non-directional, suggesting a weak relationship between both variables. The colored confidence band around the red line widens in time intervals between 40 and 80, showing high uncertainty in the trend. The graph reveals that other factors, like sectoral shifts or economic trends, influence the labor market, which consists of DS. The scatter points are widely dispersed in this graph, showing no apparent relationship between the two variables. A wide cluster-type spread of unemployment values is shown at lower time intervals of machine learning, i.e. (0-20), showing heterogeneity among those less exposed to machine learning. Both graphs show a significant spread, showing a non-linear relationship between unemployment and labor force and unemployment and labor productivity, respectively. The wide confidence band shows uncertainty in trend estimation. It shows the correlation between unemployment and FDI. Although the literature shows a negative relationship between FDI and unemployment, the graph shows that after a certain threshold of FDI, a weak relationship exists between the two variables.

Conclusion and recommendations

Integrating AI and FDI into Pakistan's economy presents transformative opportunities and multifaceted challenges. As AI continues to reshape world industries, its impact on productivity, employment, and innovation is growing obvious. In Pakistan, AI adoption has begun in sectors like manufacturing, education, agriculture, and healthcare, supported by national policies such as the Digital Pakistan and AI policies (2022). These initiatives are steps toward positioning Pakistan with global digital trends. However, Pakistan's job market remains vulnerable because of an increasing population, low productivity, low digital literacy, insufficient infrastructure, and inadequate AI-related skills, particularly in rural regions. The dual economic perspectives of the Refugee Effect and Schumpeter's Creative Destruction show the contrasting effects of AI on labor markets. The Schumpeter Effect shows AI's ability to eliminate old roles and create new opportunities through innovation. The Refugee Effect focuses on the risk of job losses passing job creation, particularly in economies with weak labor structures like Pakistan. It becomes even more pressing given the high number of low-skilled workers and the gender disparities in employment. If not managed effectively, AI deepens structural unemployment and economic inequality, displacing those who lack the skills to transition into emerging industries. To manage this transformative period, Pakistan must adopt practical strategies to confirm comprehensive and sustainable growth. The study results recommend that policies, such as the government prioritizing investment in digital infrastructure, education, and workforce upskilling, be made necessary for preparing the labor market for an AI-driven economy. Therefore, we should implement AI-focused FDI policies that include tax leaves and innovation hubs to attract global investment and create jobs. With up-to-date policymaking and inclusive digital transformation, Pakistan can connect AI and FDI to stimulate economic development, reduce unemployment, and build a resilient, future-ready workforce.

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