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Digitalization, Climate Change, and Labor Force Participation: Empirical Evidence and Policy Perspectives

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ABSTRACT

Objective:
This study examines the influence of digitalization and climate change on labor force participation in selected South Asian countries.

Research Gap:
There is very limited literature on the influence of digitalization and climate change on labor force participation in South Asian nations. The study will fulfill the gap by using advanced econometric techniques.

Design/Methodology/Approach:
The chosen time span for this analysis is from 2000 to 2023, and it uses the Cross-Sectionally Augmented Autoregressive Distributed Lag model to examine the relationship among the selected variables.

Theoretical / Practical Implications of the Findings:
The empirical findings highlight a significant interconnection among digitalization, climate change and LFP. Particularly, the use of the internet and mobile phones significantly increases LFP and female labor force participation. However, an increase in CO_2 emissions inversely affects LFP in the short and long run.

Originality/Value:
By focusing on selected South Asian nations and disaggregating total LFP into male and female LFP, the study offers valuable insights for policy practitioners.

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1. Introduction

In recent years, digital advancement and climatic variation have been key forces influencing labor force participation rates globally (Andlib & Khan, 2021). Digital advancement has recently emerged as an important element of economic development (Autor, 2019). Primarily, South Asia has reflected very low broadband subscriptions, roughly 2.75 per 100 in India and 1.36 per 100 people in Pakistan (World Bank, 2023), but mobile cellular penetration has expanded dramatically, creating new forms of labor participation through gig platforms, mobile banking, and e-commerce (Shuangshuang et al., 2023). The digital accessibility lowers standard mobility barriers, especially for the female labor force (Fernandez & Puri, 2023). The interaction of digitalization and climate change is deeply embedded within South Asia's socio-economic and demographic context (Safdar et al., 2022). GDP per capita ranges from Sri Lanka's relatively higher-income status to Nepal's low-income, migration-dependent economy, influencing job-creation capacity (Bussolo et al., 2024). Urbanization, while expanding opportunities in services and manufacturing, also strains infrastructure and reinforces informality, with mixed effects on women's participation (Andlib, 2022; Meghir et al., 2015)

The main rationale for the analysis stems from the integration of three significant facts: The shifting demographics of South Asia, the prevailing gender inequalities in the workforce, and the mutual impact of digitalization and climate change, all of which are influencing job prospects (Andlib & Khan, 2018) . Primarily, South Asia accounts for nearly 1.9 billion people of the world's population, and its workforce is increasing continuously. The demographic can serve as a potential driver of economic growth. But underutilization of the labor force can become an obstacle to economic development. The most surprising gender gap is observed in Pakistan, where female labor force participation (FLFP) is below 10 percent, whereas male labor force participation (MLFP) is above 70 percent. Policy experts recommend that FLFP keep pace with MLFP to raise economic prosperity (Andlib & Zafar, 2023).

Based on the previously mentioned scenario, the study has three specific objectives. It examines the effect of digitalization on overall labor force participation (LFP), MLFP and FLFP. It assesses how climate change variables constrain or enable labor force participation across South Asian countries. It also evaluates the role of economic, demographic, and infrastructural covariates in determining participation results.

The research is important from academic, empirical, policy, and societal fronts. Academically, it advances the literature by integrating digitalization and climate change, two structural forces often studied separately, into a unified framework for analyzing LFP. By disaggregating outcome variable into male, and female participation, it offers a gender-sensitive perspective that highlights trends often overlooked in aggregated analyses. Methodologically, the application of the cross-sectionally augmented autoregressive distributed lag model provides rigor by addressing both short- and long-run effects, whereas considering cross-sectional dependence and heterogeneity, issues particularly relevant for South Asia (Safdar et al., 2022). Moreover, the analysis closes the gap by focusing on five South Asian countries, India, Pakistan, Bangladesh, Nepal, and Sri Lanka, that mutually represent nearly a quarter of the world's population yet remain underexplored in comparative labor research.

Section 2 will present the literature review; the section 3 will elaborate on the data source and variables construction. Section 4 will discuss the econometric techniques used in the analysis. Section 5 will highlight the key empirical findings, and Section 6 will conclude the study and present policy implications based on the empirical results.

2. Empirical Literature:

In this section, we will discuss the existing literature on the impact of digitalization and climate change on LFP. (Chiplunkar & Goldberg, 2022) note that, in emerging economies, the surge in the labor force is driven by increased internet usage. The analysis employed a "difference-in-differences approach" to examine the impact of internet usage on LFP for emerging economies. However, it is observed that FLFP is particularly affected by deeper internet penetration. Authorities are required to utilize internet usage as a measure to alleviate gender disparity in LFP in developing nations. (Amber & Chichaibelu, 2023) integrate "instrumental variable techniques" to analyze the connotations among internet use and LFP. It is enlightening that mobile usage primarily improves FLFP in Pakistan. It is also advised to reduce disparities in technology availability to expand FLFP. But it is also found that academic and cultural factors are driving inequality in internet usage in a developing nation. (Bahia et al., 2023) point out that mobile use increases LFP alongside paid jobs, yet the results are affected by expertise levels in Tanzania. The analysis incorporates "panel household survey data" to investigate the relationship between the variables under discussion. (Kusumawardhani, 2023) explain that, in Indonesia, FLFP is partially driven by internet usage, but it also entails certain disadvantages, including the fact that sometimes females do not find quality jobs despite high internet penetration. The research applied "household survey data" to find out the association between these factors. Moreover, the analysis highlights that digitalization tends to encourage FLFP, but this does not always contribute to stable or permanent employment. (Abrar & Raza, 2023) demonstrate that greater internet penetration is escalating FLFP in developing nations. The study used an "ordinary least squares regression approach" to examine the impact of internet use on FLFP. (Grzybowski & Patel, 2023) adopted "panel data techniques" to determine the link between mobile usage and LFP. The study concludes that mobile usage has been observed to expand LFP in South Africa.

Several studies explore the impact of climate change, particularly temperature variations, on labor productivity and labor supply across different countries and time periods. (Somanathan et al., 2021) focused on India, using firm-level and regional data to investigate how climate change impacts labor productivity. The analysis reveals that higher heat significantly reduces productivity and increases absenteeism, thereby reducing effective labor supply, especially on hotter days. Furthermore, (Rigas & Kounetas, 2024) tend to incorporate an "instrumental technique" to examine the relationship between CO_2 emissions and LFP and highlight the negative association between environmental degradation and LFP.

Numerous analyses examine the association between renewable energy intensity and LFP, highlighting the potential for employment. (Ma & Wang, 2025) state the role of renewable energy expansion in job creation and economic development across BRICS nations from 2000 to 2023. Using Autoregressive Distributed Lag (ARDL) models, they found that investments in renewable energy significantly increase green job creation, contributing to sustainable employment growth. Similarly, (Mazorodze, 2025) assessed the impact of renewable energy consumption on employment in Sub-Saharan Africa between 1992 and 2020, utilizing the Pooled Mean Group (PMG) estimator. It discovers that LFP is enhanced by renewable energy usage. (Pilipczuk, 2024) explains that the renewable energy sector is correlated with the expansion of LFP in Poland. The study has utilized "advanced techniques "to determine the association between renewable energy and LFP. (Hernandez-Cortes & Mathes, 2025) observed that increased renewable energy use is associated with improved LFP in Brazil.

The relationship between GDP per capita and LFP has been explored by numerous studies. (Aker & Mbiti, 2010) integrate an" instrumental approach" to evaluate the correlation between GDP per capita and LFP for Africa. It shows that LFP expansion is driven by higher GDP per capita. The research has applied the "fixed-effects panel regression technique" to determine the association between these factors. (Sajid et al., 2024) find an inverse U-shaped relationship between GDP per capita and FLFP in Pakistan, demonstrating that, following an initial rise, additional growth is associated with lower FLFP until the employment obstacles are resolved. Similarly, (Ilyas et al., 2025) highlighted ap positive influence of an increase in GDP per capita on LFP in case of Pakistan.

Multiple analyses tend to inspect the interrelation between urbanization and LFP. (Jaffri et al., 2015) report that urbanization is associated with lower FLFP due to socioeconomic constraints that inhibit women's participation in Pakistan. The analysis utilized the "ARDL cointegration approach" to examine the association between the variables under discussion. (Gundogan, 2009) illustrate that urbanization decreases FLFP in Turkey. It is also noticed that prevailing social constraints limit the FLFP. The study used the "rural-to-urban migration dynamics technique" to analyze the connection between these factors. (Mitra & Tripathi, 2024) explain that the decrease in FLFP is driven by urban growth in emerging economies. (Abid, 2025) have illustrated that rapid urbanization is positively interconnected with LFP in GCC region.

The existing literature also examines the implications of higher levels of education for LFP. For instance, (Aisyi et al., 2025) utilized the "random effects panel regression method" to assess the relationship between education and LFP. Adianita et al. (2024) argue that education increases LFP. The study adopts "classical regression analysis techniques" to examine the association between education and LFP. (Lovaglio, 2026) concluded a positive connotation between education attainment and LFP in EU.

By incorporating data on how digitalization and climate change affect labor force participation, this literature review demonstrates that while LFP is typically supported by digital access, such as internet and cellphone usage. It also emphasizes that extreme climate variations are inversely interconnected with LFP. Furthermore, the review expands the research by incorporating GDP per capita, education, urbanization, and renewable energy as significant factors associated with LFP. All things considered, the study offers a solid foundation for creating an all-encompassing framework to investigate LFP more thoroughly, particularly in the context of developing nations.

3. Data Sources, Variables Construction and Methodology

3.1. Data Sources
The analysis has taken five South Asian countries, including India, Pakistan, Bangladesh, Nepal, and Sri Lanka, to explore the influence of climatic variation and digitalization on LFP. The study spans 23 years (2000–2023). The data regarding the study are extracted from World Development Indicators. The variable descriptions are given in Table 1.

Table 1: Description of Variables

Variable	Definition	Source	Expected Effect on dependent variables
Dependent variables			
LFP	Population (15+ years of age) engaged in or seeking for employment	World Bank (WDI),	Dependent variable
MLFP	Male population (15+ years of age) engaged in the labor force	WDI	Dependent variable
FLFP	Female population (15+ years of age) engaged in the labor force	WDI	Dependent variable
Independent variables **Digitalization**			
Fixed broadband subscriptions (FBB)	Subscriptions per 100 people	WDI	Positive
Mobile cellular subscriptions (MCS)	Subscriptions per 100 people	WDI	Positive
CO_2 emissions (COE)	Metric tons per capita	WDI	Negative
Renewable energy intensity (REI)	Total renewable energy consumption from various sources	WDI	Positive
Covariates			
GDP per capita (GDC)	GDP per capita - constant (2015)	WDI	Mixed
Urban population (URP)	Urban population as percentage of total population	WDI	Positive
Education level (EDU)	% of population with tertiary education	WDI	Positive

3.2 Methodology

The research has included some important variables to investigate the impact of climatic variations and digitalization on LFP, MLFP and FLFP in selected South Asian nations. The selected variables are abbreviated as FBB (fixed broadband subscriptions), MCS (mobile cellular subscriptions), COE (CO_2 emissions), REI (renewable energy intensity), GDC (GDP per capita), URP (urban population), and EDU (education level). This is further elaborated by the following functional forms.

$$\mathrm{LFP_{pt}} = f(\mathrm{FBB_{pt}}, \mathrm{MCS_{pt}}, \mathrm{COE_{pt}}, \mathrm{REI_{pt}}, \mathrm{GDC_{pt}}, \mathrm{URP_{pt}}, \mathrm{EDU_{pt}}) \quad (1)$$
$$\mathrm{MLFP_{bt}} = f(\mathrm{FBB_{bt}}, \mathrm{MCS_{bt}}, \mathrm{COE_{bt}}, \mathrm{REI_{bt}}, \mathrm{GDC_{bt}}, \mathrm{URP_{bt}}, \mathrm{EDU_{bt}}) \quad (2)$$
$$\mathrm{FLFP_{gt}} = f(\mathrm{FBB_{gt}}, \mathrm{MCS_{gt}}, \mathrm{COE_{gt}}, \mathrm{REI_{gt}}, \mathrm{GDC_{gt}}, \mathrm{URP_{gt}}, \mathrm{EDU_{gt}}) \quad (3)$$

The regression forms are presented in Equation (4) with regard to the current analysis. ε_{pt} , μ_{bt} and μ_{gt} are the error terms, and γ_{pt} , ϑ_{bt} and ω_{gt} are cross-section specification terms.

$$\mathrm{LFP_{pt}} = \varpi_{1pt} + \varpi_{2pt}\mathrm{FBB_{bt}} + \varpi_{3pt}\mathrm{MCS_{bt}} + \varpi_{4pt}\mathrm{COE_{pt}} + \varpi_{5bt}\mathrm{REI_{pt}} + \varpi_{6bt}\mathrm{GDC_{pt}} + \varpi_{7pt}\mathrm{URP_{pt}} + \varpi_{8pt}\mathrm{EDU_{pt}} + \gamma_{pt} + \varepsilon_{pt} \quad (4)$$
$$\mathrm{MLFP_{bt}} = \varphi_{1bt} + \varphi_{2bt}\mathrm{FBB_{bt}} + \varphi_{3bt}\mathrm{MCS_{bt}} + \varphi_{4bt}\mathrm{COE_{bt}} + \varphi_{5bt}\mathrm{REI_{bt}} + \varphi_{6bt}\mathrm{GDC_{bt}} + \varphi_{7bt}\mathrm{URP_{bt}} + \varphi_{8bt}\mathrm{EDU_{bt}} + \vartheta_{bt} + \mu_{bt} \quad (5)$$
$$\mathrm{FLFP_{gt}} = \Theta_{1gt} + \Theta_{2gt}\mathrm{FBB_{bt}} + \Theta_{3gt}\mathrm{MCS_{bt}} + \Theta_{4gt}\mathrm{COE_{bt}} + \Theta_{5gt}\mathrm{REI_{gt}} + \Theta_{6gt}\mathrm{GDC_{gt}} + \Theta_{7gt}\mathrm{URP_{gt}} + \Theta_{8gt}\mathrm{EDU_{gt}} + \omega_{gt} + \mu_{gt} \quad (6)$$

For this study, the natural logarithm of the selected economic indicators is used to reduce the issue of skewness in the data.

The analysis has used second-generation panel unit root tests that account for cross-sectional dependence to examine the stationarity of the variables. In particular, the Cross-sectionally Augmented IPS (CIPS) test developed by (Pesaran, 2007) is employed. This approach is appropriate considering the presence of cross-sectional dependence (CD) among the panel units. Further, the study employs the (Westerlund & Edgerton, 2008) panel cointegration test, which also accounts for cross-sectional dependence and structural breaks.

3.3 Cross-Sectionally Augmented Autoregressive Distributed Lag Model

The study has used the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model proposed by (Pesaran, 2007) to estimate both short- and long-run associations. The CS-ARDL model has many advantages over other modern econometric techniques. It addresses the problems of cross-sectional dependence, structural breaks and slope heterogeneity. Moreover, the CS-ARDL model accommodates variables integrated of order I(0) and I(1), making it suitable for the current study.

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$$D_{p,t} = \sum_{b=0}^{n_g} q_{b,p} D_{p,t-1} + \sum_{b=0}^{n_w} e_{b,p} S_{p,t-1} + r_{p.t} \tag{7}$$

The Autoregressive Distributed Lags model is elucidated by Equation (7); however, it generates a biased outcome in the presence of CD. Nonetheless, the research applies a cross-sectional average of each regressor in Eqn (8) (Chudik & Pesaran, 2015).

$$D_{p,t} = \sum_{b=0}^{n_g} q_{b,p} D_{p,t-1} + \sum_{b=0}^{n_w} e_{b,p} S_{p,t-1} + \sum_{b=0}^{n_k} \acute{y}_{p,}, A\bar{C}_{p,t-1} + r_{p.t} \tag{8}$$

$D_{p,t-1} = (E_{p,t-1}, G_{p,t-1})$ denotes the averages of the response economic indicators LFP, MLFP, and FLFP, and controlled economic indicators FBB, MCS, COE, REI, GDC, URP, EDU, ng, n_w, and n_k are lags of each economic indicator in Eqn (9).

CSARDL model is presented in Eqn (9)

$$\widehat{\omega}_{csardl,p} = \frac{\sum_{b=0}^{n_w} \hat{\mathfrak{g}}_{M,p}{}^{nz}}{1 - \sum_{b=0}} \widehat{\Upsilon_{B,r}} \tag{9}$$

The long-run coefficients and mean group estimates are as follows.

$$\widehat{\widehat{\omega}}_{sx} = \frac{1}{n} \sum_{p=1}^{n} \widehat{\lambda_r} \tag{10}$$

The short-run coefficients are

$$\triangle D_{p,t} = \phi_p \left[D_{p,t-1} - e_p S_{p,t}\right] \sum_{b=0}^{n_g} q_{b,p}, \triangle D_{p,t-1} + \sum_{b=0}^{n_w} e_{b,p} \triangle_b S_{p,t-1} + \sum_{b=0}^{n_k} \acute{y}_{p,}, AC_{p,t-1}$$
$$+ r_{p.t} \tag{11}$$

Where

$b = t - (t - 1)$

Besides, short-run coefficients are,

$$\hat{\mathfrak{t}}_p = \left(1 - \sum_{b=1}^{n_g} \widehat{\Upsilon_{B,r}}\right) \tag{12}$$

$$\widehat{\omega}_p = \frac{\sum_{b=0}^{n_w} \hat{\mathfrak{g}}_{b,p}}{\hat{\mathfrak{t}}_r} \tag{13}$$

$$\widehat{\widehat{\omega}}_{sx} = \frac{1}{n} \sum_{p=1}^{n} \widehat{\Upsilon_r} \tag{14}$$

In this study, long-run coefficients reflect the equilibrium impact of independent variables on labor force participation after the system has fully adjusted, whereas short-run coefficients capture immediate responses to shocks or changes in the predictors.

4. Results and Discussion

The study discusses the empirical findings of the impact of digitalization, climate change and renewable energy on labor force participation regarding selected South Asian countries. The descriptive statistics of the measured variable are represented in Table 2. The mean values of the LFP rate, MLFP, and FLFP are 4.02, 4.37, and 3.48,respectively. It is found that a stable average LFP rate indicates that labor markets are experiencing moderate fluctuations rather than unexpected changes. Whereas a higher MLFP mean value reflects standard workplace setups, a lower FLFP mean value indicates that female work decisions are contingent on prevailing socio-economic barriers.

Additionally, the standard deviations of LFP rate, MLFP, and FLFP are 0.12, 0.08, and 0.31, respectively, indicating variation across the labor force. A medium spread in the digital indicators demonstrates unequal access to technological advancement across economies. Furthermore, dispersion in urbanization and renewable energy highlights variations in development stages and infrastructure development across selected nations. The variation observed in education indicates inefficient growth in human resources. The CO_2 emissions value reflects fluctuating interactions with adverse environmental factors that harm workers' overall well-being.

Table 2. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
LFP	4.02	0.12	3.78	4.25
MLFP	4.37	0.08	4.21	4.50
FLFP	3.48	0.31	2.74	4.04
FBB	1.55	0.49	0.18	1.86
MCS	4.63	0.18	4.12	4.91
COE	3.53	1.50	0.91	4.34
REI	3.06	0.58	1.13	4.07
GDC	9.61	2.54	6.59	10.63
URP	4.16	0.18	3.48	4.51
EDU	4.14	0.23	3.36	4.49

To check the CD, the study has adopted the CD test developed by Pesaran (2015). The research has rejected the null hypothesis and discovered that all variables regarding the designated economies are cross-sectionally dependent.

Table 3. Cross-Sectional Dependence (CD) Analysis

Variable	Test Statistic (p-value)
LFP	17.82*** (0.00)
MLFP	16.94*** (0.00)
FLFP	18.37*** (0.00)
FBB	14.56*** (0.00)
MCS	15.88*** (0.00)
COE	20.11*** (0.00)
REI	13.72*** (0.00)
GDC	19.04*** (0.00)
URP	12.69*** (0.00)
EDU	14.23*** (0.00)

***, **, * denotes level of significance at 1%, 5% and 10% respectively

The unit root tests established by Pesaran (2015) and (Bai & Carrion-I-Silvestre, 2009) are depicted in Table 4. The outcomes demonstrate that at the level, the analysis cannot reject the null hypothesis. Stationarity was checked using first differences. Consequently, the null hypothesis was rejected, indicating that all measured variables are stationary at first differences. Thus, fixed broad subscriptions, mobile cellular subscriptions, CO_2 emissions, renewable energy intensity, GDP per capita, urban population, and education level are found to be stationary at first difference.

Table 4. CIPS Unit Root Test

Variable	I(0)	I(1)
LFP	−2.01	−4.36***
MLFP	−2.18	−4.52***
FLFP	−1.74	−4.11***
FBB	−2.87**	−5.68***
MCS	−3.12***	−5.94***
COE	−1.63	−4.29***
REI	−2.41**	−5.21***
GDC	−1.96	−3.88***
URP	−2.54**	−5.47***
EDU	−2.79**	−5.83***

***, **, * illustrates significance at 1%, 5% and 10% respectively

The study has adopted Swamy's slope homogeneity test, developed by (Pesaran, 2007), and subsequently applied the CD and unit root tests. This test is mainly useful for detecting whether slope coefficients are homogeneous or heterogeneous across all three models. The null hypothesis states that the slope coefficients are homogeneous, whereas the alternative hypothesis states that they are heterogeneous. Table 5 indicates that the analysis confirmed the alternative hypothesis, indicating that slopes are heterogeneous at the 1% significance level across three models. The consistent rejection of slope homogeneity across overall, male, and female groups verifies the validity of these results across all three models.

Table 5. Slope Heterogeneity Test

Model	Dependent Variable	Delta tilde	Delta tilde adjusted
Model 1	LFP	9.84*** (0.00)	11.26*** (0.00)
Model 2	MLFP	10.91*** (0.00)	12.08*** 0.00)
Model 3	FLFP	13.47*** (0.00)	14.92*** 0.00)

***, **, * illustrates significance at 1%, 5% and 10% respectively

Afterwards, by determining the order of integration, the research focuses on appropriate techniques to analyze the persistent associations between the specified variables. The analysis incorporates tests introduced by (Westerlund & Edgerton, 2008) for the three models. The test's primary purpose is to determine whether multiple issues are present, including heterogeneity, serial correlation, structural breaks, and cross-sectional dependence. The null hypothesis states that the specified variables are not cointegrated. Moreover, the cointegration estimation approach developed by (Westerlund & Edgerton, 2008) discovered that the selected variables are cointegrated. The test findings are valid, as it tends to reject the null hypothesis of no cointegration for the overall, male, and FLFP samples. Moreover, uniform significance across Gt, Ga, Pt, and Pa statistics validates the prevalence of those long-run relationships. Therefore, it is uncovered that, considering the selected Asian nations, a long-term interaction prevails between the designated variables.

Table 6: Westerlund Panel Cointegration Test

Model	Gt	Ga	Pt	Pa
Model 1 (LFP)	−3.87***	−6.21**	−5.74***	−9.46***
Model 2 (MLFP)	−3.62***	−5.89**	−5.31***	−8.97**
Model 3 (FLFP)	−4.14***	−6.88***	−6.02***	−10.83***

***, **, * illustrates significance at 1%, 5% and 10% respectively

The CS-ARDL results are shown in Table 7. With a coefficient of 0.011, the results show that fixed broadband subscriptions (FBB) have a favorable impact on LFP. This suggests that since better internet connectivity increases access to knowledge, digital platforms, and job prospects, a 1% increase in FBB results in a 0.011% increase in the LFP rate. With a value of 0.008, mobile cellular subscriptions (MCS) also have a favorable impact on LFP. Because mobile technology facilitates communication through financial inclusion, and job hunting, this implies that a 1% increase in mobile subscribers raises the LFP rate by 0.008%. The results align with the existing literature; for instance, (Grzybowski & Patel, 2023) have illustrated the favorable relationship between internet penetration and labor force participation in the context of developing economies.

With a value of 0.010, which means that a 1% increase in REI causes a 0.010% increase in the LFP rate, renewable energy intensity (REI) also has a positive impact on LFP. The growth of renewable energy promotes environmentally friendly job possibilities and sustainable economic activity. The results are consistent with the prior literature in labor and environmental economics. For instance, (Pilipczuk, 2024) demonstrated that increased use of renewable energy is positively associated with LFP.

Similarly, GDP per capita (GDC), with a coefficient of 0.016, considerably increases LFP. This suggests that, since economic growth promotes infrastructure construction, industry expansion, and job creation, a 1% increase in GDP per capita results in a 0.016% increase in LFP.

With values of 0.006 and 0.015, respectively, urban population (URP) and education (EDU) also exhibit positive correlations with LFP. LFP grows by 0.006% and 0.015% for every 1% increase in urban population and education. Education increases human capital, skills, and productivity, enabling workers to access markets, transportation, and employment opportunities. (Apostu et al., 2024) also underscore the positive interconnection between URP and LFP. On the other hand, there is a negative connotation between CO_2 emissions and LFP. A 1% increase in CO_2 emissions results in a 0.015% decrease in LFP. Environmental degradation reduces worker productivity and creates economic uncertainty, deterring people from entering the workforce. (Rigas & Kounetas, 2024) highlighted the negative connotation between environmental degradation and LFP. The CS-ARDL results show that, while other factors continue to have favorable effects, CO_2 emissions remain negatively interconnected with LFP in the short term. With a negative coefficient of −0.41, the error correction term (ECT) shows convergence toward the long-run equilibrium.

Digitalization considerably improves both male and female labor force participation (MLFP and FLFP), with a greater effect on FLFP, according to the CS-ARDL data. By creating job opportunities, GDP per capita and renewable energy intensity also have a favorable impact on MLFP and FLFP. In a similar vein, education and urbanization increase access to resources and skills, thereby boosting labor market participation.
While CO_2 emissions lower MLFP and FLFP, digitalization, renewable energy, GDP per capita, urbanization, and education continue to raise them in the short term. Convergence toward equilibrium is confirmed by the error correction term values of −0.37 for MLFP and −0.46 for FLFP.

Table 7: CS-ARDL (Long Run and Short Run) Analysis

Variable	LFP LR	LFP SR	LFP LR	LFP SR	LFP LR	LFP SR
FBB	0.011** (0.02)	0.019** (0.03)	0.008** (0.03)	0.014** (0.04)	0.016*** (0.00)	0.028*** (0.00)
MCS	0.008** (0.03)	0.014** (0.04)	0.006** (0.04)	0.010** (0.05)	0.011** (0.01)	0.019** (0.02)
COE	−0.015*** (0.00)	−0.028*** (0.00)	−0.012*** (0.00)	−0.021*** (0.00)	−0.021*** (0.00)	−0.038*** (0.00)
REI	0.010** (0.01)	0.019** (0.02)	0.009** (0.01)	0.016** (0.02)	0.013*** (0.00)	0.024*** (0.00)
GDC	0.016*** (0.00)	0.029*** (0.00)	0.017*** (0.00)	0.031*** (0.00)	0.014*** (0.00)	0.026*** (0.00)
URP	0.006** (0.03)	0.010** (0.04)	0.005** (0.04)	0.009** (0.05)	0.007** (0.02)	0.012** (0.03)
EDU	0.015*** (0.00)	0.028*** (0.00)	0.012*** (0.00)	0.022*** (0.00)	0.023*** (0.00)	0.041*** (0.00)
ECT (−1)	—	−0.41*** (0.00)	—	−0.37*** (0.00)	—	−0.46*** (0.00)

***, ** and * depicts the level of significance at 1 percent, 5 percent and 10 percent respectively

The results from Dumitrescu and Hurlin's (2012) causality test for three dependent variables are illustrated in Table 8. The analysis observed that there prevails a unidirectional interconnection between all the selected independent variables and LFP, MLFP and FLFP.

Table 8. Dumitrescu and Hurlin (2012) Heterogeneous Panel Causality Test

Null Hypothesis	Statistic	p-value
FBB → LFP	19.842***	0.000
LFP → FBB	0.691	0.312
MCS → LFP	17.406***	0.001
LFP → MCS	0.528	0.401
COE → LFP	23.915***	0.000
LFP → COE	0.884	0.247
REI → LFP	15.774***	0.003
LFP → REI	0.463	0.359
GDC → LFP	21.602***	0.000
LFP → GDC	2.981	0.084
URP → LFP	14.318***	0.004

LFP → URP	0.577	0.343
EDU → LFP	26.118***	0.000
LFP → EDU	0.739	0.298
FBB → MLFP	16.233***	0.002
MLFP → FBB	0.514	0.419
MCS → MLFP	14.908***	0.004
MLFP → MCS	0.476	0.356
COE → MLFP	20.647***	0.000
MLFP → COE	0.791	0.281
REI → MLFP	13.386***	0.006
MLFP → REI	0.622	0.337
GDC → MLFP	24.302***	0.000
MLFP → GDC	2.714	0.099
URP → MLFP	12.947***	0.007
MLFP → URP	0.601	0.329
EDU → MLFP	22.581***	0.000
MLFP → EDU	0.684	0.305
FBB → FLFP	25.764***	0.000
FLFP → FBB	0.806	0.268
MCS → FLFP	22.118***	0.000
FLFP → MCS	0.592	0.341
COE → FLFP	29.487***	0.000
FLFP → COE	0.973	0.214
REI → FLFP	18.964***	0.001
FLFP → REI	0.447	0.372
GDC → FLFP	20.331***	0.000
FLFP → GDC	3.284	0.071
URP → FLFP	15.802***	0.003
FLFP → URP	0.658	0.318
EDU → FLFP	31.206***	0.000
FLFP → EDU	1.124	0.198

***, ** and * depicts the level of significance at 1 percent, 5 percent and 10 percent respectively

5. Conclusions and Policy Implications

The study aims to evaluate the influence of climate change and digitalization on LFP regarding five South Asian countries. It has employed the CSARDL methodology to assess the association between the selected variables, with the time period from 2000 to 2023. It reveals a strong association between all independent variables and LFP. Moreover, the analysis found that internet and mobile use are responsible for boosting LFP in the selected sample nations. Renewable energy intensity is observed to favourably impact LFP in both the short and long runs. In contrast, CO_2 emissions tend to lessen FLFP. Considering other factors, education, urbanization, and GDP per capita promote FLFP, underscoring their key role in encouraging females to pursue job opportunities. It is evident that all independent variables have a unidirectional association with LFP.

The analysis argues that digital infrastructure is a key factor in elevating female labor force participation across South Asian countries. There are multiple mechanisms that tend to lessen mobility constraints and improve access to job prospects. These mechanisms include expanding broadband access, increasing mobile connectivity, and expanding digital platforms. It is recommended that governments should finance digital infrastructure in rural and undeveloped regions, promote digital literacy programs, and support digital employment platforms. Moreover, policy experts should focus on developing policies that reduce the prevalent gender gaps in labor force participation. Additionally, governments should integrate digital skills training into education systems, thereby strengthening labor market participation by improving human capital and employment.

Furthermore, the analysis primarily accentuates that environmentally friendly policies play an important role in labor force participation. As observed, climate variability and environmental degradation adversely affect labor force participation by reducing productivity and causing economic instability. Therefore, policy experts should dedicate funds towards workplace safety measures and climate-resilient infrastructure to protect workers from environmental shocks. In addition, the positive impact of renewable energy intensity on labor force participation illustrates that the shift towards environmentally friendly growth tends to generate novel employment opportunities. Governments are advised to fund environmentally friendly sectors and provide technical training programs related to green job opportunities.

Moreover, South Asian countries should promote employment, gender inclusion, and sustainable economic development through integrating digital development policies and climate adaptation strategies.

The analysis has provided multiple insights for future research. Primarily, labor force survey data can be used to examine the impacts of technological and environmental factors on the labor force across diverse employment opportunities and economic sectors. Moreover, future studies can integrate absolute measures of environmental impact, including weather fluctuations and the incidence of disasters, to accurately assess environmental threats. It is suggested that future analysis be elaborated by highlighting the interrelationship between technological advancement and renewable energy, as these factors mutually encourage labor participation. The study can be extended to integrate developed economies for a comprehensive examination of these factors. The above-mentioned strategies can enhance the understanding of how environmental factors and technological advancements mutually affect labor markets during periods of significant societal shifts.

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