Journal Homepage: -www.journalijar.com

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR)

ISSN (O): 2320-5407
ISSN (P): 3107-4928

Article DOI:10.21474/IJAR01/23894
DOI URL: http://dx.doi.org/10.21474/IJAR01/23894

RESEARCH ARTICLE

ANALYZING WOMEN'S LABOR FORCE PARTICIPATION IN KARNATAKA USING THE SHRUG DATASET

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Manuscript Info

Manuscript History
Received: 16 May 2026
Final Accepted: 18 June 2026
Published: July 2026

Abstract

This study examines the determinants of Women's Labor Force Participation (WLFP) in Karnataka using 2011 Census data and regression analysis across 27,211 observations. The study evaluates the influence of various socioeconomic, demographic, and geographic factors. The results show that while all variables are statistically significant, their explanatory power is limited, indicating that WLFP is shaped by multiple interacting factors. Female and male literacy rates and healthcare availability are negatively associated with WLFP, while scheduled caste population, greater distance from towns, and higher proportions of unirrigated land are positively associated with WLFP. Overall, the findings suggest that women's labor force participation in Karnataka is shaped by a combination of economic, geographic, and social factors rather than development indicators alone. This highlights the need for policies that address the barriers to women's employment.

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Introduction:-

Women's labor force participation (WLFP), defined as the involvement of working – age women in the economy through either being employed or actively seeking employment, is an important indicator of economic development, gender equality, and social inclusion. Despite India's sustained economic growth over the past two decades, female labor force participation has remained comparatively low, creating a significant economic and social puzzle. This decline has occurred alongside rising wages, falling fertility rates, and improvements in education and development indicators — factors that would traditionally be expected to increase women's participation in paid employment. Understanding this paradox is essential for evaluating the relationship between economic growth, social change, and women's access to employment opportunities. India's experience demonstrates that the relationship between education and women's employment is not straightforward. While education can improve skills, aspirations, and access to jobs, rising education and household income have also been associated with women withdrawing from low-skilled agricultural or informal work when suitable formal employment opportunities are limited.

This reflects the broader "U-shaped" relationship between female education and labor force participation, where women with low education participate due to economic necessity, women with intermediate education may withdraw due to social expectations and limited opportunities, and highly educated women may re- enter through professional employment. Karnataka is selected as a case study because it has a rural female literacy rate above the national rural average, suggesting stronger educational attainment and greater potential for women's economic participation. Additionally, its comparatively lower rural village population, relative to highly rural-populated states,

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allows for a more focused analysis of the relationship between education, economic opportunities, and women's labor force participation. States with extremely large rural populations often have highly diverse rural economies, making it difficult to identify clear relationships. Karnataka has a significant rural population but is not among the largest rural-population states like Uttar Pradesh, Bihar, or Rajasthan. This allows for more focused analysis while still studying rural women's employment patterns. Although Karnataka has relatively strong female literacy, its economic structure is diverse, with strong services, technology, and mixed rural economies. This makes it a useful case study for investigating how different economic opportunities and structural factors affect WLFP. Existing studies on female labor force participation in India often rely on national-level trends, which can overlook local differences in economic structure, social norms, and access to opportunities.

A more disaggregated analysis is therefore necessary to understand the factors shaping women's participation at regional levels. This paper also uses the SHRUG dataset which is aggregated at the level of an identifier called a 'shrid'. The 'shrid' is equivalent to a single village or town. The usage of the SHRUG dataset is not commonly seen in existing papers for this topic. The study examines the influence of female and male literacy, Scheduled Caste population share, healthcare availability, and distance from towns on WLFP in Karnataka using 2011 Census data from the SHRUG dataset and regression analysis. By analyzing these factors together, the study aims to identify the structural and social forces that explain variation in women's workforce participation and contribute to a deeper understanding of the relationship between development and female employment in India.

Review of Literature:-

There have been several studies on the topic of women's labor force participation in various countries. Avista Nur Aini and Muhammad Arif (2025) studied determinants of female labor force participation rate between 2019 and 2023 in 34 provinces of Indonesia. The paper investigated various socioeconomic factors that affected WLFP, aiming to analyze and find the correlation between each factor and the labor force participation. The authors have used various panel data econometric models, as well as Chow and Hausman tests to determine that the Fixed Effect Model (FEM) was the most appropriate model to use in the study. Based on this model, it was found that 98.05% of changes in the WLFP can be explained by socioeconomic status, where the marital status of women ages 20-24 is not significant. Further, the paper argued that there should be policies to overcome social and cultural barriers to help foster gender equity in the workplace, childcare support, and community engagement programs. Subrata Saha, Arifa Sultana, and Sanjoy Kumar Saha (2022) studied the determinants of female labor force participation in Tangail district in Bangladesh using a logistic regression analysis. The study identifies and analyzes various individual, socio-economic, and household factors that have an effect on female participation in the labor force.

To conduct the research various methods were used such as the Logistic Regression Model, Hosmer and Lemeshow test of goodness of fit, and Cooks Distance Method. Based on these methods it was found that women in nuclear families participate more in economic activities than joint families and that the age of a woman, until age 55 years, has a positive relation with economic activities. Further, women with higher levels of education are more likely to participate, with married women participating less than the unmarried, divorced, and widowed. The paper argued that government policies which allow greater access to education, bigger training facilities in rural areas, and policies for women's safety should be created to increase WLFP. The study undertaken by Suliman Alghamdi and Rozina Shaheen (2024) looks at low WLFP in Saudi Arabia, aiming to identify the demographic, social, economic, and educational aspects that influence women' s participation in the labor force. The study takes into consideration demographic variables such as fertility rates, age, economic factors, and social factors such as urbanization. The study aims to analyze these factors using methods such as the Augmented Dicky-Fuller Test, Regression Analysis, Jarque-Bera Test, and the Variance Inflation Factor.

Based on the methods used, it was found that higher inflation rates, urban population growth rates, and larger age dependency ratios lead to increased female participation, GDP growth, school enrollment, and fertility rate do not have a significant effect. The paper advised that job creation programs, educational policies, and policies that take care of urbanization issues should be created by the government, as well as measures taken to reduce gender biased discrimination. Mattias Busso and Dario Romero Fonseca (2014) studied the determinants of female labor participation. They analyzed and identified various factors that have been grouped into three main categories. Education, marriage, and fertility make up the first group, socioeconomic and environmental factors being the second group, and the third group comprises how decisions are made in different types of households. The study uses household surveys over 30 years and 15 countries, as well as a decomposition analysis and panel econometric models. From this, it was found that improvements in women's education lead to increased participation in the labor force and that women with younger children participate less, showing that fertility decisions and family structure influences WLFP. Additionally, the results showed that growth in WLFP slowed down after 2000 indicating that there were barriers such as discrimination that limited the growth. An Lie and Inge Noback (2010) studied determinants of regional female labor market participation in the Netherlands, where they aimed to identify the causes for the differences in WLFP in different regions.

This was done by analyzing municipality data, using observable variables such as female unemployment rate, and latent variables such as education levels. To conduct the study, various methods were used such as Spatial Structural Equation Model (SEM), Lagrange Multiplier tests, and the Maximum Likelihood (ML) estimations. Based on this, it was found that the proportion of higher educated females and house ownership were both less important indicators of socio-economic status than disposable income. Further, it was found that the positive determinants of female participation were socio-economic status, the age range of 35-45, male unemployment, and the presence of female dominated sectors. The paper argued that several policy changes such as making it more financially appealing for women to join the workforce and more childcare opportunities could be made. Febriano Aulia Nur Rahmawan and Siti Aisyah (2024) studied determinants of women’s labor participation rate in developing Asian countries and the five main factors that affect female labor participation in six developing Asian countries. The factors include impact of women’s involvement in parliament, women’s education, female entrepreneurship, etc. The study has been done to make economic development in developing Asian countries better and more sustainable. To conduct the research, several models such as the panel data analysis method, pooled least squares, and the Chow test and Hausman test were used.

From the determined Fixed Effects Model (FEM) approach, it was found that women’s involvement in the parliament has a positive and significant impact on the female labor force participation rate, while female unemployment had a negative and significant effect on participation levels. It was also found that women’s education, fertility rates, etc. did not have a significant effect on WLFP. The paper argues that policies such as ones to increase women’s involvement in politics through quotas and training can be taken. Further, to increase women’s employment, policies such as business incentives, and establishments of empowerment institutions can be considered. Prof. Özlem Taşseven, Prof. Dr. Dilek Altaş, and Asst. Prof. Turgut Ün (2016) studied the determinants of female labor force participation in OECD countries identifies and analyzes the socio-economic, demographic, and cultural factors that are seen in the rising female labor participation rate in OECD countries. The paper goes through the different countries and highlights how each one has experienced a different level of WLFP due to its culture, education, and social norms. It analyzes 5 main factors including labor market characteristics, educational backgrounds, economic factors, etc. To conduct the research, the authors utilized the panel logit model, SVAR model, Granger Causality Test and linear probability model estimation.

From the tests conducted, it was seen that when combined the OECD countries show an increase in WLFP due to the increase in part-time employment amongst women. It was also found that unemployment rate, GDP per capita, and fertility rate all affect the participation rates positively. Further, it was found that cost of child care and family structure are some of the most important factors affecting women’s participation in the labor force. Based on this the paper argues for policies for work and family life to be created. Harry A. Sackey (2005) studied female labor force participation in Ghana and the effects of education. This paper examines female labor force participation and fertility patterns in Ghana in the 1990s. It is written by Harry A. Sackey and published in 2005. The study also analyzes how education, household structures, and socioeconomic factors influence WLFP. The research studies demographic, socioeconomic, and community factors that impact women’s participation in the labor market. To conduct the study, the author used probit and multinomial logit techniques, Wald test, Ordinary least squares technique, and the Hausman test.

Based on these it was found that the agriculture sector is the main industry in which women decide to work in, allowing for the WFLP rates to be high. Additionally, education has a positive impact on WFLP suggesting that policies such as education of females to be improved should be made. This would allow the gender gap in education to decrease and more women will broaden their employment opportunities. Pietro Giorgio Lovaglio and Adalgisa Perrelli (2024) studied individual and regional determinants of women’s participation in the European labor market. The study takes place in Italy, France, and Germany, and it aims to identify the factors that lead to unequal employment rates in the three countries. It analyzes factors such as demographics, family and social factors, and regional factors, and compares the findings to identify the causes of WLFP in the three countries. The methods used are multilevel modelling, aggregated data, and likelihood ratio statistics. The study showed that factors such as age, marital status, and number of people in the family affect WLFP. In Germany it was seen that women with children showed higher risks for unemployment, but these risks decreased as the children grew older. Further, in Italy it was seen that higher education levels increase employment and in France the correlation between age and marital status with labor force participation was highest. The paper argues that policies such as rewards/benefits for working mothers should be taken, as well as a movement towards implementing inclusion and awareness policies against gender discrimination. Helen Iweagu, Denis N. Yuni, Chukwudi Nwokolo, and Andenyangtso Bulus (2015) studied determinants of female labor force participation in Nigeria. The study identifies and analyzes the factors that affect WLFP in rural and urban regions of Nigeria. It aims to analyze the factors that differentiate between WLFP in urban and rural settings. The aim is to understand the different socioeconomic, demographic, and cultural factors that influence whether a woman in Nigeria joins the labor force or not.

The methods used to conduct the study are the logit function, logit model equation, and logit regression. The study found that the older a woman is, the less likely she is to participate in the labor force. However, in rural regions, age is not a determining factor of WLFP, but marital status has a positive effect on WLFP. Further, religion and literacy rate showed a negative relationship with WLFP, while the poverty rate had a significant impact on the labor force in rural regions. In urban regions, it was seen that marriage, religion, and poverty rate had an insignificant impact, but age has a positive relationship with WLFP. The paper argues that policies for education, living conditions, and scholarships can be created for women in rural regions. Dr. Joginder Singh, Dr. Bharat Bhushan, Vandana Sethi, and Ajad Singh (2020) examined workforce participation and labor market shifts in Karnataka between 1993 and 2021 following the 1991 economic reforms. Using data from several National Sample Survey Office (NSSO) rounds and employing a Logit model to calculate odd ratios, the study identifies key socio-demographic determinants of engagement. The findings indicate a significant reduction in the overall Labor Force Participation Rate from 71.7% to 59.1% with many gender disparities where women remain underrepresented.

The analysis shows that although family size negatively impacts participation, having more jobs within a household and being in the 30-44 age bracket increases employment likelihood, with education proving more influential in urban areas. The paper concludes that despite economic growth, structural and gender imbalance point towards targeted policy interventions to create equitable employment opportunities. Dr. Shamika Ravi and Dr. Mudit Kapoor (2024) analyzed the significant resurgence of the female Labor Force Participation Rate (LFPR) across Indian states and sectors between 2017-18 and 2022-23. Utilizing unit level data from about 2.5 million individuals in the Periodic Labour Force Survey (PLFS) and employing Generalized Additive Models (GAMs) with a logit link function, the study investigates how age, marital status, and the presence of children influence labor market engagement.

The findings indicate a substantial rise in rural female LFPR from 24.6% to 41.5%, while urban participation experienced lesser growth from 20.4% to 25.4%. The analysis reveals that female participation typically follows a bell- shaped curve peaking between 30 to 40 years of age. However, this is hindered by marriage and presence of children under 14, especially in urban areas. The paper concludes that this recent growth reflects the impact of government initiatives such as Mudra loans and Self- Help Groups, suggesting that while the resurgence supports a women-led development model, persistent interstate and rural-urban disparities require further rigorous research to fully understand the underlying reasons. Though there have been several studies related to women’s labor force participation, there are several research gaps. In order to address some of these research gaps, the present study deals with certain objectives.

Objective:-

This study aims to examine the socioeconomic, demographic, and geographic factors influencing women’s labor force participation (WLFP) in Karnataka using a data-driven approach. Using village-level data from the SHRUG (Socioeconomic High-resolution Rural- Urban Gradients) dataset, the study investigates how the following factors contribute to variations in women’s participation in the workforce. The research seeks to identify key patterns and structural factors that influence WLFP and improve understanding of the barriers and conditions affecting women’s economic participation in Karnataka.

Hypothesis:-

1. Female and male literacy, which are socioeconomic factors, will affect WLFP in a positive way. An increase in the literate population is expected to correspond with an increase in employment.
2. Scheduled castes, which is a socioeconomic category, should impact WLFP in a positive way. This is because SC households usually have high participation in the labor force due to economic necessity.

3. Doctors in position, which is a socioeconomic factor, should have a positive effect on WLFP. More doctors can lead to better childcare and healthcare for women. This should increase women's participation in the labor force.
4. Distance to the nearest town, a geographical factor, should have a negative correlation on WLFP. Typically, towns have more employment opportunities. The nearer a town is, the easier it is for women to travel and work in the labor force.
5. Unirrigated land, a geographic factor, can have a positive correlation on WLFP. Generally, irrigated regions will have better agricultural income, so women may not need to participate in the labor force.

Data and Methodology:-

This study adopts a quantitative, cross-sectional research design to examine the determinants of women's labor force participation (WLFP) in Karnataka. The unit of analysis is the village, allowing for variations at a local level that may not be visible in broader national or state-level analyses to be studied. The analysis is based on multiple linear regression, estimated using Microsoft Excel's regression analysis tool. Microsoft Excel was chosen as it is easy and accessible to use. It is widely available and it is suitable for standard linear regression analysis. The study uses village - level data drawn from the SHRUG (Socioeconomic High resolution Rural - Urban Gradients) dataset, which links multiple Indian government data sources. For this paper, data from the village directory (2011) and population census abstract (2011) was used. These datasets were used as they provide comprehensive village-level information on literacy, caste composition, infrastructure, and demographic characteristics for the state of Karnataka. The dependent variable is women's labor force participation. This variable was a proxy created by taking the proportion of total female working population over the total female population for each village.

The independent variables are as follows:-

- **Female Literacy Rate:** Proportion of literate female to total female population in the village
- **Male Literacy Rate:** Proportion of literate male to total male population in the village. This variable was taken to assess whether household level education effects differ by gender.
- **Scheduled Caste (SC):** Proportion of the scheduled castes female population over the total female population, used as a proxy to indicate social composition and its relationship with women's work participation
- **Doctors in Position:** Measure of doctors positioned/stationed in the village, as recorded in the SHRUG dataset. This is a variable to measure for local healthcare infrastructure and access.
- **Distance from Towns:** Measures as the village's distance (in km) from the nearest town. The dataset was split into distances 0-10 kilometers and then distances greater than 10 kilometers.

The relationship between WLFP and its determinants is estimated using an Ordinary Least Squares (OLS) multiple linear regression model. Separate OLS regressions were estimated to evaluate the individual association between WLFP and each explanatory variable. One additional multivariate regression including female and male literacy was estimated to examine their joint effects. The regression was estimated using Excel's Data Analysis ToolPak, which generates coefficient estimates, standard errors, t-statistics, p-values, and the model's R^2 and adjusted R^2 values. This study employs a pooled OLS specification across all 27,211 villages in Karnataka without district or regional fixed effects. While fixed effects could help control for unobserved district level heterogeneity (such as local governance quality of regional economic shocks), they were not incorporated here due to the scale of the dataset and the constraints of the analytical tool used.

Table 1: Regression Table of Female Literacy Rate and WLFP

Regression Statistics	
Multiple R	0.165423213
R Square	0.027364839
Adjusted R Square	0.027329093
Standard Error	0.181484072
Observations	27211
ANOVA	

	df	SS	MS	F	Significance F			
Regression	1	25.21346592	25.21347	765.5181959	3.39E-166			
Residual	27209	896.1683703	0.032936					
Total	27210	921.3818362						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.543954956	0.004565992	119.1318	0	0.535005379	0.552904534	0.535005379	0.552904534
0.527777778	-0.229078213	0.008279537	-27.668	3.3941E-166	-0.245306528	-0.212849897	-0.245306528	-0.212849897

Source: Compiled by the author using SHRUG Data (2011)

Referring to Table 1, female literacy rate has a statistically significant but very weak relationship with women's labor force participation in Karnataka in 2011. The regression has an R² value of 0.0274 (2.74%) meaning that female literacy explains only 2.74% of the variation in women's labor force participation. This indicates that literacy does not influence WLFP alone, rather it shows that there are other factors that might better explain it. The p- value of 3.394E-166 shows that the relationship is statistically significant and extremely unlikely to have occurred by chance; however, this can be due to the large sample size of 27, 211 observations. In a case like this, even a small relationship can become statistically detectable. The key interpretation is that the relationship is real, but has limited practical explanatory power.

The coefficient of -0.229 shows a negative relationship, which means that as female literacy increases, WLFP decreases. This finding may appear surprising; however, it reflects a well-documented pattern in Indian labor economics The findings could be explained with the 'Income Effect', mainly seen in middle-income groups. In the year 2011, in Karnataka, as women became more educated, their families withdrew them from the labor force. A more literate household earns more overall, which reduces the necessity for women to work. This theory can also be referred to as the 'Household Prestige Paradox', which also accounts for how working women were sometimes seen as a signal of poverty, so wealthier and more educated households kept women at home as a sign of higher social status. The U-shape relationship between female education and labor force participation could also be a reason for these findings. It explains that women with very low education often participate in the workforce, usually agricultural or manual labor, due to economic necessity.

As education increases, many women temporarily exit the workforce because they face social expectations, lack suitable qualifications, or lack access to formal jobs. At higher education levels, women re-enter through professional employment. Karnataka in 2011 was likely in this middle stage, where rising literacy led women to leave low-skilled work, but they did not have enough education to be absorbed by formal employment opportunities. Policies should try to encourage improvements in female education with expanded access to employment opportunities and implement measures that reduce social and cultural barriers to women's workforce participation.

Table 2: Regression Table of Male Literacy Rate and WLFP

Regression Statistics	
Multiple R	0.111708653
R Square	0.012478823
Adjusted R Square	0.012442529
Standard Error	0.18286759

Observations	27211								
ANOVA									
	df	SS	MS	F	Significance F				
Regression	1	11.497761	11.49776	343.8269	2.7668E-76				
Residual	27209	909.8840752	0.033441						
Total	27210	921.3818362							
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%	
Intercept	0.548208772	0.006930976	79.09547	0	0.534623704	0.56179384	0.534623704	0.56179384	
0.731958763	-0.1831383	0.009876641	-18.54257	2.77E-76	-0.202497017	-0.16377957	-0.202497017	-0.163779573	

Source: Compiled by the author using SHRUG Data (2011)

Male literacy rate also shows a statistically significant but extremely weak relationship with women's labor force participation (WLFP) in Karnataka in 2011, as shown in Table 2. The statistical metrics such as the R^2 value of 0.0125 (1.25%), shows that male literacy explains only 1.25% of the variation in WLFP. This is even lower than the female literacy's explanatory power (2.74%). This indicates that male literacy alone provides little information about whether women participate in the workforce. The remaining variation could be explained by factors such as household income, caste, and local employment opportunities. The very low p-value (2.7668E-76) confirms that the negative relationship is statistically significant and unlikely due to chance, but because of the large sample size (2.7668E-76), the effect is statistically detectable despite being practically weak. The coefficient of -0.183 indicates that as male literacy increases, women's labor force participation decreases. To explain this, the male breadwinner income effect can be used. The effect states that higher male literacy is associated with higher earnings and more stable employment, allowing households to withdraw women from low-paid or physically demanding work once their income is sufficient. This could also reflect social expectations, where economically secure households may view women staying at home as a sign of status.

Higher male education may also strengthen traditional gender norms and increase restrictions on women's visible participation in work. Additionally, districts with higher male literacy in Karnataka, such as urban and semi-urban areas, often had fewer opportunities for the types of informal and agricultural work that rural women traditionally performed, while formal jobs suitable for educated women were limited. These findings suggest that improving male literacy alone is unlikely to increase women's labor force participation; policies should instead focus on directly addressing barriers faced by women entering the workforce. The weaker relationship compared to female literacy occurs because male literacy is an indirect factor affecting WLFP. Female literacy is linked to women's skills, aspirations, and ability to access employment, whereas male literacy can affect women's participation through household income, social norms, and family decisions.

Table 3: Regression Table of Scheduled Castes and WLFP

Regression Statistics								
Multiple R	0.041211125							
R Square	0.001698357							
Adjusted R Square	0.001661667							
Standard Error	0.183863036							
Observations	27211							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	1	1.564835163	1.564835	46.2892074	1.04138E-11			
Residual	27209	919.8170011	0.033806					
Total	27210	921.3818362						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.413621584	0.001590939	259.9858	0	0.410503262	0.416739906	0.410503262	0.416739906
1	0.036877379	0.005420261	6.803617	1.0414E-11	0.026253391	0.047501367	0.026253391	0.047501367

Source: Compiled by the author using SHRUG Data (2011)

The regression in Table 3 examines the relationship between Scheduled Caste (SC) population share and women's labor force participation (WLFP) in Karnataka using 2011 Census data (27,211 observations). It is the weakest model among the three regressions, with an R^2 value of only 0.0017 (0.17%), meaning SC population share explains almost none of the variation in WLFP. The Adjusted R^2 being nearly identical confirms that this result is genuine rather than a statistical issue. However, the very small p-value (1.04E-11) and significant F-statistics show that the relationship is statistically significant, meaning it is unlikely to have occurred by chance. However, the effect remains practically very weak. Unlike the literacy regressions, the coefficient is positive (+0.037), meaning areas with a higher SC population share tend to have slightly higher female labor force participation. This may reflect economic and social factors, as SC households have historically had higher participation in wage labor due to economic necessity and fewer opportunities to rely on household income alone. However, the effect is very small because SC communities in Karnataka are highly diverse, ranging from economically disadvantaged rural areas to urban SC middle-class households, making SC share alone an incomplete measure of women's employment behavior. Other factors such as local industries, household income, childcare responsibilities, land ownership, and access to jobs have a much stronger influence on WLFP. Additionally, reservation policies might have contributed to the growth of an SC middle class. This could have resulted in women withdrawing from work due to improved economic status and social expectations. The findings highlight the importance of reducing economic inequalities and expanding employment opportunities, especially for socioeconomically disadvantages communities.

Table 4: Multivariate Regression Table (Female Literacy Rate, Male Literacy Rate and WLFP)

Regression Statistics								
Multiple R	0.169761544							
R Square	0.028818982							
Adjusted R Square	0.028747592							
Standard Error	0.18135169							
Observations	27211							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	2	26.55328624	13.27664	403.6873	0			
Residual	27208	894.82855	0.032888					
Total	27210	921.3818362						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.509134219	0.007112003	71.58802	0	0.495194328	0.52307411	0.495194328	0.52307411
0.527777778	-0.30211132	0.014120194	-21.39569	9.9E-101	-0.329787624	-0.27443502	-0.329787624	-0.27443502
0.731958763	0.106695805	0.016716512	6.382659	1.77E-10	0.073930585	0.139461024	0.073930585	0.13946102

Source: Compiled by the author using SHRUG Data (2011)

The multivariate regression in Table 4 examines how female and male literacy rates together predict women's labor force participation (WLFP) in Karnataka using 2011 Census data (27, 211 observation). The model is statistically significant with an R^2 of 0.0288 (2.88%), meaning both literacy variables together explain only a small proportion of the variation in WLFP. Although the F-statistic (403.69) and near-zero Significance F confirm that the relationship is not due to chance, the low explanatory power shows that literacy alone remains a weak predictor of women's workforce participation. When both the variables of female literacy and male literacy rate are included, one variable either suppresses or partially confounds the other. Female literacy becomes more strongly negative (coefficient: -0.302 compared to -0.229 previously), suggesting that when male literacy is held constant, higher female literacy is associated with lower WLFP. This supports the idea of an education–participation paradox, where educated women in Karnataka increasingly left low-skilled agricultural or manual work but did not enter formal employment due to limited employment opportunities. It may also reflect social expectations, where educated women were more likely to prioritize household responsibilities or avoid informal work considered below their qualifications. Interestingly, male literacy changes from a negative relationship to a positive coefficient (+0.107) when female literacy is controlled for. This suggests that the earlier negative association was mainly because male and female literacy tend to rise together, and it was female education that was driving the decline in WLFP. Once this overlap is removed, higher male literacy appears to slightly increase women's participation, possibly because more educated men may support women's employment, have better access to urban labor markets, or live in areas with improved infrastructure and opportunities for women. These findings show that since higher literacy does not always correlate to higher women's labor force participation, policies should focus on closing the gap between education to employment by implementing vocational training, formal job creation, and workplace support for women.

Table 5: Regression Table of Doctors in Position and WLFP

Regression Statistics								
Multiple R	0.07955239							
R Square	0.006328583							
Adjusted R Square	0.006292063							
Standard Error	0.183436152							
Observations	27211							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	1	5.831041161	5.831041	173.2910941	1.86679E-39			
Residual	27209	915.5507951	0.033649					
Total	27210	921.3818362						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.425337275	0.001152629	369.015	0	0.423078064	0.427596486	0.423078064	0.427596486
1	-0.04638249	0.003523433	-13.164	1.86679E-39	-0.0532886	-0.039476384	-0.0532886	-0.039476384

Source: Compiled by the author using SHRUG Data (2011)

Table 5 examines the relationship between doctors in position and women's labor force participation (WLFP) in Karnataka. The model is statistically significant, with a very small R^2 value of approximately 0.0063 (0.63%). This means that doctors in position explain less than 1% of the variation in WLFP. The extremely low p-value (1.87E-39) and high F-statistic (173.29) confirm that the relationship is statistically real and unlikely to occur by chance; however, the effect is practically weak. The coefficient of -0.046 shows that as the number of doctors in position increases, WLFP slightly decreases. This negative relationship follows the pattern seen with literacy variables, where indicators of development are associated with lower female labor force participation. The negative relationship is likely because doctors in position act as a proxy for overall development and institutional presence rather than healthcare alone. Areas with more doctors in Karnataka in 2011 were generally more urbanized, economically developed, and had stronger public infrastructure. These same areas often had higher household incomes, allowing families to withdraw women from low-paid or physically demanding work, creating a “Household Prestige” effect. In less developed regions with weaker healthcare systems, women often participated in labor out of economic necessity, especially through agriculture and informal work. Better healthcare may also reduce “distress labor,” where women enter the workforce because of financial shocks caused by illness or poor access to medical services. Since doctors in position appears to reflect broader levels of development rather than just healthcare, policies should focus on ensuring that economic development creates accessible and suitable employment opportunities for women.

Table 6: Regression Table of Distance (0-10km) to the Nearest Town and WLFP

Regression Statistics								
Multiple R	0.07739356							
R Square	0.00598976							
Adjusted R Square	0.00586554							
Standard Error	0.17894579							
Observations	8004							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	1	1.544046254	1.544046	48.218903	4.1102E-12			
Residual	8002	256.2368152	0.032022					
Total	8003	257.7808614						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.35788078	0.005711229	62.66266	0	0.34668528	0.369076274	0.346685283	0.36907627
0	0.0054715	0.000787948	6.943983	4.11E-12	0.00392692	0.007016084	0.003926916	0.00701608

Source: Compiled by the author using SHRUG Data (2011)

This regression examines the relationship between distance to the nearest town and women’s labor force participation (WLFP) among villages within 0–10 km of towns in Karnataka. The model seen in Table 6 is statistically significant, with an R^2 of 0.0060 (0.60%), meaning distance explains only a small proportion of the variation in WLFP. The extremely low p-value (4.11E-12) and significant F-statistic (48.22) confirm that the relationship is statistically real, but the small R^2 shows that distance alone is a weak predictor of women’s workforce participation. The coefficient of +0.005 indicates that as villages become slightly farther from towns, WLFP increases, which is a meaningful finding despite the small effect size. This positive relationship could be explained by the urban shadow effect, where villages closest to towns are influenced by urban social norms, and greater emphasis on women’s education and household roles. Peri-urban villages often shift away from agriculture, which reduces opportunities for women in traditional farm-based work, while formal employment opportunities are still difficult to access due to transport, safety, and qualification barriers. As a result, women near towns may be stuck between rural and urban economies, leaving them less likely to participate in the workforce. Villages slightly farther away retain stronger agricultural systems where women’s labor is more economically necessary and socially accepted. The pattern is also linked to household and geographic factors. Near towns, men are more likely to commute for work, infrastructure is better, and household incomes are generally higher, reducing the need for women's income contribution. In contrast, villages further away may depend more heavily on women's agricultural labor, local wage work, and schemes such as MGNREGA. Therefore, the negative effect of being close to towns does not correlate with the statement that towns reduce employment directly; rather, it reflects the broader transition from necessity-based rural work to a more developed economy where women have fewer incentives or opportunities to participate. The low R^2 highlights that distance to towns is only one factor influencing WLFP. Women's labor force participation in Karnataka is shaped by many factors including literacy, caste, land type, household income, and childcare responsibilities. The low intercept (0.358) is significant because it suggests that villages located immediately next to town had the lowest predicted WLFP, backing the claim that urban influence and changing social norms reduced women's participation near town boundaries. These findings suggest that improving proximity to urban centers alone is not enough to increase WLFP unless it is accompanied by policies that improve access to safe transportation, formal employment, and skills development.

Table 7: Regression Table of Distance (>10km) and WLFP

Regression Statistics								
Multiple R	0.06978086							
R Square	0.00486937							
Adjusted R Square	0.00481746							
Standard Error	0.18418838							
Observations	19172							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	1	3.182285079	3.182285	93.80254	3.91818E-22			
Residual	19170	650.3491569	0.033925					
Total	19171	653.531442						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.39771792	0.00382056	104.0994	0	0.390229288	0.40520655	0.390229288	0.405206554
10.5	0.00166809	0.000172232	9.685171	3.92E-22	0.001330505	0.00200568	0.001330505	0.002005684

Source: Compiled by the author using SHRUG Data (2011)

This regression, in Table 7, examines the relationship between distance from the nearest town (beyond 10 km) and women's labor force participation (WLFP) in Karnataka's remote rural areas. The model is statistically significant, with an R^2 of 0.0049 (0.49%), meaning distance explains less than 1% of the variation in WLFP. The extremely low p-value (3.92E- 22) and high F-statistic (93.80) confirm that the relationship is real and unlikely to be due to chance, but the small R^2 shows that distance alone is a weak predictor. The coefficient of +0.002 indicates that as villages become more remote, WLFP continues to increase, although the effect is smaller than in the 0–10 km distance model. The positive relationship is likely to occur because remote villages in Karnataka are more dependent on agriculture and necessity-based employment. Villages further than 10 km from towns, particularly in northern Karnataka, often had rain-fed agriculture, higher SC/ST populations, lower incomes, and fewer formal employment opportunities. In these areas, women's work was essential for household survival through farming, livestock care, wage labor, and schemes such as MGNREGA. Male migration from remote villages also increased women's responsibility for managing farms and household livelihoods, contributing to higher measured WLFP. The weaker coefficient compared to the 0–10 km model reflects a flattening effect. Near towns, small increases in distance greatly reduce the influence of urban norms and the "urban shadow effect," causing a sharp rise in WLFP. Beyond 10 km, settlements are already fully rural, so further distance adds little additional change because agricultural dependence and rural labor patterns are already established. The higher intercept (0.398 compared to 0.358 in the 0–10 km model) confirms that WLFP is higher once villages move beyond the immediate influence of towns. Since higher women's labor force participation in remote areas seems to be driven my economic necessity, policies should focus on improving the quality and diversity of employment rather than simply increasing labor force participation.

Table 8: Regression Table of Unirrigated Land and WLFP

Regression Statistics								
Multiple R	0.05342557							
R Square	0.00285429							
Adjusted R Square	0.00281764							
Standard Error	0.18375656							
Observations	27211							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	1	2.629892766	2.629893	77.88474	1.15645E-18			
Residual	27209	918.7519435	0.033766					
Total	27210	921.3818362						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.40502058	0.002159296	187.5707	0	0.400788247	0.409252908	0.400788247	0.409252908
0.59938294	0.03632195	0.004115693	8.825233	1.16E-18	0.028254982	0.044388921	0.028254982	0.044388921

Source: Compiled by the author using SHRUG Data (2011)

The regression in Table 8 examines the relationship between the share of unirrigated land and women's labor force participation (WLFP) in Karnataka. The model shown is statistically significant, with an R^2 of 0.0029 (0.29%), meaning that unirrigated land explains only a very small proportion of the variation in WLFP. However, the extremely low p-value (1.16E-18) and significant F-statistic (77.88) confirm that the relationship is real and not due to chance. The coefficient of +0.036 shows that areas with a higher proportion of unirrigated land tend to have higher female labor force participation. This positive relationship may be explained by the role of rain-fed agriculture and economic necessity. Unirrigated areas in Karnataka, especially in northern districts, depend heavily on agriculture that is vulnerable to rainfall uncertainty. Crops grown in these regions often require significant manual labor, with women contributing through farming, harvesting, and wage labor. Since Census data counts both main and marginal workers, even seasonal agricultural work can contribute to measured WLFP. Unirrigated land can also signal economic vulnerability. Households dependent on rain-fed farming face unstable incomes and cannot afford to keep women outside the workforce.

Therefore, women may have to participate as unpaid family workers or agricultural wage laborers to help support their household. This accounts for some of the similarity between the unirrigated land and SC population models, since both capture aspects of poverty, social disadvantage, and economic compulsion. However, irrigated regions usually have more stable agricultural incomes and greater economic security. This allows families to withdraw women from low-paid agricultural work, reflecting the “prestige withdrawal” pattern in literacy and developmental indicators, where higher prosperity can reduce a woman’s labor participation. Overall, while the effect is statistically significant, the low R^2 shows that land type alone cannot explain WLFP, which can be influenced by many other factors such as household income, caste, crop type, migration, and local employment opportunities. The intercept (0.405) suggests that areas with little or no unirrigated land have a lower baseline WLFP, supporting the idea that agricultural vulnerability increases women’s participation mainly through economic necessity. The findings suggest that policies should promote climate- resilient agriculture, rural livelihood diversification, and access to higher-quality employment so that women’s labor force participation is driven by opportunity rather than economic necessity.

Limitations:-

This study relied on proxies for the regressions, since the SHRUG dataset does not provide many variables which can be directly used. Women’s labor force participation (WLFP) proxy was constructed using the ratio of total female working population to total female population at the village level. Since the dataset did not provide information about the age distribution in the female working population and the total population, the ratio may include the population of female children. The proxy may understate or distort the gender-specific dynamics the study aims to capture. Similarly, female and male literacy rates, Scheduled Caste population share, and unirrigated land were all constructed as proxy variables rather than drawn directly from pre-defined indicators in the dataset. Unirrigated land was used as a proxy for agricultural dependency and local economic conditions, on the assumption that villages with a higher share of unirrigated land face greater agricultural instability, lower productivity, and potentially different labor demand patterns for women compared to villages with better irrigation infrastructure.

However, this is an indirect measure: unirrigated land share does not capture other important dimensions of local economic structure, such as the presence of non- agricultural employment, market access, or seasonal labor migration, which may also shape WLFP independently of irrigation status. Because each of these variables is a constructed proxy rather than a direct measure of the underlying concept it represents, there is a risk of measurement error, and the true relationships between these constructs and WLFP may be imperfectly captured by the regression results. Across all regression models, including both the near-town and far-from-town sub-samples, the R^2 values were low, indicating that the included variables explain only a small portion of the variation in WLFP across villages. This suggests that female and male literacy, SC population share, healthcare availability (proxied by number of doctors), and unirrigated land are not, on their own, sufficient to explain why WLFP varies so substantially across Karnataka's villages.

As noted in the methodology, the decision to split the sample by distance from town (≤10 km and >10 km) was necessary to obtain interpretable regression results, but this approach has its own limitations. It reduces the sample size within each sub-group, prevents direct statistical comparison of coefficients across the two models, and relies on a 10 km cutoff that, while empirically motivated, is ultimately a simplification of what may be a more continuous or non-linear relationship between distance from town and WLFP. Additionally, since the data is from a single point in time, the analysis shows relationships between variables but cannot prove that one factor directly causes changes in WLFP. Second, the model does not account for local differences between districts, such as variations in job opportunities, governance, or cultural practices, which may influence the results. Third, the use of 2011 Census data means the findings may not fully represent recent changes in Karnataka’s economy and society. Finally, some important factors affecting WLFP, such as household decision-making and social attitudes towards women working, are difficult to measure and are not included in the analysis as there were no direct variables nor proxy variables that could be created to measure these in the SHRUG dataset.

These missing factors may explain why the model accounts for only a small part of the variation in WLFP. Excel’s ToolPak is limited to only basic linear and multiple linear regressions, but other industry leading regression applications such as SAS, SPSS, etc. include different types of regressions such as non-linear or logistic regressions. Additionally, the user interface on SAS and SPSS is more intuitive and built for statistics, offering better data tools and automated charts, which Excel lacks. Furthermore, multicollinearity and heteroscedasticity are not directly available in Excel – further steps would have to be taken to calculate the Variance Inflation Factors (VIFs) to check for multicollinearity and conduct other tests such as the White test to find heteroscedasticity. Furthermore, the SHRUG dataset did not include some relevant variables to women's labor force participation such as marital status, household income, number of children etc. Since these variables could not be included in the regression models, the relationships found in this paper may have omitted variable bias. Also, it should be noted that the dataset taken is from the year 2011, so some of regression analysis may or may not still be applicable in more recent years.

Conclusion:-

This study examined the socioeconomic, demographic, and geographic factors influencing women's labor force participation (WLFP) in Karnataka using village-level data from the SHRUG dataset based on the 2011 Census of India. Using OLS regression models, the study analyzed the relationship between WLFP and indicators including literacy, Scheduled Caste population share, healthcare availability, unirrigated land, and distance from towns.

Below are the findings for the hypotheses based on the data analysis using the SHRUG 2011 Datasets:-
Hypothesis 1: Female and male literacy, which are socioeconomic factors, will affect WLFP in a positive way. An increase in the literate population is expected to correspond with an increase in employment. Based on the data analysis, female literacy has strong relationship with WLFP (due to the low p-value) but showed a negative association indicated through the negative coefficient. Given the data, the hypothesis cannot be accepted. Continuing Hypothesis 1 on the effect of male literacy on WLFP, data suggests that this factor is negatively associated with WLFP as shown by the negative coefficient. So, Hypothesis 1 cannot be accepted for the positive influence on WLFP.

Hypothesis 2: Scheduled castes, which is a socioeconomic category, should impact WLFP in a positive way. This is because SC households usually have high participation in the labor force due to economic necessity. Based on the data, this hypothesis can be accepted since the Scheduled Caste population share showed a positive relationship with WLFP as indicated by the positive coefficient.

Hypothesis 3: Doctors in position, which is a socioeconomic factor, should have a positive effect on WLFP. More doctors can lead to better childcare and healthcare for women. This should increase women's participation in the labor force. This hypothesis should not be accepted since the data suggests that this factor is negatively associated with WLFP due to the negative coefficient.

Hypothesis 4: Distance to the nearest town, a geographical factor, should have a negative correlation on WLFP. Typically, towns have more employment opportunities. The nearer a town is, the easier it is for women to travel and work in the labor force. The hypothesis should not be accepted since the data shows that there is a positive relationship between distance to the nearest town and WLFP, supported by the positive coefficient.

Hypothesis 5: Unirrigated land, a geographic factor, can have a positive correlation on WLFP. Generally, irrigated regions will have better agricultural income, so women may not need to participate in the labor force. The data analysis supports the hypothesis since there is a positive relationship between WLFP and unirrigated land as shown by the positive coefficient.

In summary, the findings show that while all variables were statistically significant, they explained only a small proportion of variation in WLFP. This suggests that women's workforce participation in Karnataka is influenced by a combination of structural, economic, and social factors rather than any single development indicator. Female literacy had the strongest relationship with WLFP but showed a negative association, supporting the education–participation paradox where increased education does not always translate into higher employment. As education rises, women may withdraw from low-skilled work due to changing aspirations, household income effects, and limited access to suitable formal employment. Similarly, male literacy and healthcare availability were negatively associated with WLFP, reflecting larger development patterns where higher incomes and improved infrastructure reduce dependence on women's labor. In contrast, unirrigated land and Scheduled Caste population share showed positive relationships with WLFP, suggesting that participation is often driven by economic necessity in poorer rural areas. Women in these regions are more likely to engage in agricultural and informal work because household survival depends on their contribution.

The distance-based analysis further highlighted the role of geography. Villages further from towns showed slightly higher WLFP, while areas closer to towns had lower participation, suggesting an "urban shadow" effect where changing social norms and higher household incomes reduce women's participation without necessarily providing employment opportunities. Overall, the study demonstrates that increasing literacy, infrastructure, or development alone may not be sufficient to improve WLFP in Karnataka. Policies must focus on creating suitable employment opportunities, improving access to formal jobs, reducing mobility barriers, and addressing social factors influencing women's work decisions. However, the findings are limited by the use of proxy variables, cross-sectional 2011 data, and the inability to capture household-level factors such as income and social attitudes. Future research using recent data and more advanced methods could provide a deeper understanding of changing patterns in women's employment.

The positive associations of scheduled caste concentration and unirrigated land with WLFP suggest that high WLFP in Karnataka's districts reflects hardship rather than opportunity. To improve this, rather than trying to further increase participation rates in already high WLFP zones, policy should focus on improving wages, working conditions, and employment security for women already working. The distance regressions consistently identified the 0– 10 km peri-urban zone as having the lowest baseline WLFP in the dataset indicating that there is a plausible gap in this zone even accounting for SHRUG's limitations. Policy can dedicate employment infrastructure in Karnataka's peri-urban belts such as women's employment facilitation centers. This would address the structural trap where women are too close to towns to do agricultural work but too far to access urban formal employment. The findings in this paper match the findings seen in various international papers. The conclusion that female literacy rate will show a negative relationship with women's labor force participation is seen in the paper written by Helen Iweagu, Denis N. Yuni, Chukwudi Nwokolo, and Andenyangtso Bulus (2015).

In the paper by Febriano Aulia Nur Rahmawan and Siti Aisyah (2024), they concluded that women's education did not have an effect on WLFP, which is similar to the findings from this paper which showed a low explanatory power to female literacy rate and its effects on WLFP. However, Pietro Giorgio Lovaglio and Adalgisa Perrelli's (2024) paper highlighted that higher education levels increase employment, which is a direct contrast to the findings of this paper which show that there is a negative correlation between education (by the variable of female literacy rate) and women's labor force participation. As the research in this paper took place using the SHRUG dataset where all variables are measured at the village level, the regression results reflect ecological correlations between village-level aggregates and should not be interpreted as causal relationships operating at the level of individual women.

The findings in this paper reflect spatial patterns rather than confirmed causal mechanisms, thus the policy recommendations are framed as directional suggestions informed by spatial patterns and supported by broader literature. Future research on WLFP should repeat the analysis using recent datasets and compare the results from those found using 2011 datasets to analyze how the trend has changed and what the reasons for that change are. Additional variables such as marital status, household income, the effect of the internet and digital access, and influence of government policies should be taken into consideration when analyzing the factors of WLFP.

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