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Analysis of Poverty Determinants in Pakistan: Insights from Household-Level Data

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Abstract

The study identifies different household-level determinants of poverty in Pakistan. The study makes use of PSLM (Pakistan Social and Living Standard Measurement) data for the year 2019–2020. By evaluating the Logit and Probit regression models, this study identifies economic factors that contribute to poverty. According to the findings, poverty is positively correlated with the dependence ratio and the number of people with disabilities. In addition, households with literate household heads have lower rates of poverty. Similarly, household heads in urban areas are more likely to have lower levels of poverty than rural residents. Moreover, Sindh has the highest level of poverty, whereas KP has the lowest. Therefore, poverty may be decreased by offering free education, job opportunities, and good planning for population expansion. Because family size has a direct impact on the dependency ratio, governmental efforts to reduce household size must be encouraged. In a similar manner, rehabilitation programs should be created, and monthly transfer payments should be provided to people with disabilities. Therefore, initiatives must be taken to reduce the disparities in the country's infrastructure, health, and education.

Keywords: Poverty, Pakistan, Education, Disability, Household size, Dependency ratio

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1. Introduction

Poverty is multidimensional and can therefore be understood through several complementary measures. However, one of the most frequently used approaches is the monetary poverty line, which identifies individuals or households whose income, expenditure, or consumption falls below the resources required to meet basic needs (Manjengwa et al., 2016). Poverty also involves material deprivation, limited access to essential services, and insufficient resources for an acceptable standard of living (Bossert et al., 2013). Similarly, Ullah and Routray (2007) and Akinbobola and Saibu (2004) discuss poverty in relation to inadequate income and consumption. These approaches provide an important basis for distinguishing the monetary measure used in the present study from the wider, multidimensional experience of deprivation. Although a monetary threshold allows consistent classification of households as poor or non-poor, it cannot capture every dimension of household disadvantage.

According to estimates from the World Bank, more than two million people in Pakistan are now considered to be living below the poverty line, increasing the country's poverty rate from 4.4% to 5.4% in 2020. The WB forecast that Pakistan's poverty rate was 39.3% in 2020–21, would stay at 39.2% in 2021–22, and might drop to 37.9% by 2022–23 using the lower-middle income poverty rate, according to The News International. Using the upper-middle-income poverty rate, the global financial institution calculated that poverty stood at 78.4 percent in 2020-21, 78.3 percent in 2021-22, and is expected to fall to 77.5 percent in 2022-23. According to the World Bank, 40% of Pakistani families experienced moderate to severe food insecurity. In 2014, around 40% of Pakistan's total population experienced multidimensional poverty, while in 2018 the poverty headcount ratio in Pakistan, at the international 1.90 US$ per person per day poverty line, was around 4.4% (World Bank, 2018). Moreover, the poverty scenario in Pakistan can also be understood from the statistic that in 2016 around 44% (22.8 million) of Pakistan's child population within the age cohort of 5–16 years were estimated to be unable to join school due to poverty UNICEF (2016). Furthermore, as many as 75 out of every 1000 infants in Pakistan before the age of five due to inadequate health facilities (World Bank, 2018). These numbers show that poverty is a major problem for a developing economy like Pakistan; hence, it is important to investigate the macroeconomic factors that contribute to poverty in this nation. According to United Nations Development Programme (2020), Pakistan's population had a poverty rate of 23% in 1987–1988, 28% in 1996–1997, 30% in 1998–1999, 33% in 2004–2005, 38% in 2010–2011, 38% in 2015–2016, and 37% in 2018–2019.

Table 1: Population Below Poverty Line

Years	1987-1988	1996-97	1998-99	2004-2005	2010-2011	2015-2016	2018-019
Poverty trend in PK	23%	28%	30%	33%	38%	38%	37%

Note: Calculated by the author

Global poverty is unevenly distributed across regions. The source figures cited in the manuscript estimate approximately 902 million people living below the poverty line and report poverty incidences of 32.2% in sub-Saharan Africa, 13.5% in South Asia, 6.6% in Latin America, and 4.1% in East Asia and the Pacific. However, these figures refer to different geographic populations and should be interpreted alongside their source years and poverty measures. The source also reports that 37% of Pakistan's population was below the poverty line, with poverty incidence differing between urban (12.5%) and rural (30.5%) areas. Provincial estimates cited from the Government of Pakistan (2018) are 32.5% for Punjab, 43% for Sindh, 50% for Khyber Pakhtunkhwa, and 71% for Balochistan. In addition, the COVID-19 pandemic contributed to heightened economic insecurity, and the United Nations Development Programme (2020) highlighted associated poverty risks in Pakistan. Because these estimates may use distinct definitions, sampling periods, and sources, they are best treated as contextual statistics rather than directly comparable measurements. Therefore, the household-level regression analysis below adopts its own stated poverty classification and examines associations within the survey data.

Previous research has examined household poverty in particular provinces, districts, and population groups in Pakistan (Cheema & Sial, 2014; Guriro et al., 2019; Khan et al., 2020; Waheed et al., 2020). These studies demonstrate the importance of socioeconomic characteristics, demographic composition, and geographical conditions in explaining differences in household welfare. However, evidence from particular localities does not necessarily describe the distribution of poverty-related characteristics across the wider household population. Therefore, the present study examines household-level correlates of poverty using the Pakistan Social and Living Standards Measurement (PSLM) 2019–2020 survey. In addition to household-head characteristics and the dependency ratio, the analysis considers distinct functional limitations related to seeing, hearing, walking, remembering, self-care, and communication. This combined assessment provides a more detailed account of the association between disability and household poverty while retaining a comparison across provinces and rural and urban residences. Logit and Probit models are used to estimate associations with binary poverty status. The findings are intended to inform discussion of social protection, educational access, employment opportunities, and the geographical distribution of public services, rather than to establish causal effects from cross-sectional observations.

This analysis contributes by considering several classes of household disadvantage together within the same PSLM-based empirical framework. In particular, the inclusion of functional limitations distinguishes disability-related vulnerability from conventional measures of age, schooling, dependency, and place of residence. Similarly, comparing the two binary-response specifications allows the direction of estimated associations to be examined across modelling approaches. These contributions should be understood as descriptive and associational rather than causal, since the survey captures household circumstances within a single observation period (Cheema & Sial, 2014; Majeed & Malik, 2015; Rosano et al., 2009).

2. Literature Review

Over the past few decades, three theoretical approaches to understanding the causes of poverty have been offered: macro or structural level, micro or individual level (Bradshaw, 2007). Rapid technological advancements or fundamental economic changes accompanied by significant unemployment and displacement might lead to poverty (Teitz & Chapple, 1998). People's varying investments in education and training yield proportional returns in the job market, and human capital is the stock of productive skills, talents, health, and knowledge embedded in the labor force (Becker, 1964). According to the human capital hypothesis, poverty results from "inadequate human capital of the labor force, which results in reduced productivity and incapacity to compete for work in the rising sector that pays sufficient salaries" (Teitz & Chapple, 1998). Unlike labor economists, who attribute poverty to differences in human capital investment and its return in the labor market, sociologists propose "social capital" and increasingly focus on how a lack of social capital contributes to the prevalence of poverty. Bourdieu (2011) defines social capital as "the accumulation of real potential resources that are connected to ownership of a more or less formalized network of mutual acquaintance or recognition". By offering various types of social support (Vu 2010) and leveraging resources, ideas, and information beyond regular community connections (Knack 1999), social capital can serve as a coping mechanism in the face of poverty. Status attainment focuses on how one's place in society is influenced by both achieved and ascribed traits, such as parental background, age, race, gender, and handicap (Blau & Duncan 1967). Poverty, a negative economic consequence, is unequally distributed among educational levels, age groups, gender groups, and ethnicity groups. A life event argument, which views poverty as a life-cycle risk connected to particular life events, has questioned the social stratification approach's view of poverty as permanent and hierarchical (Leisering, 2003; 2011). The emergence of the life event approach to studying poverty is linked to an increase in "new social risk" due to labor market and family formation changes in the post-industrial era (Taylor-Gooby, 2004).

Islam and Alam (2018) report that neither gender nor religion significantly affects whether a household in Bangladesh is in poverty. The main determinants of poverty status, however, include age, rural-urban distribution, education, marital status, disability, remittances, and regional

differences. The most effective way to reduce poverty is through education and training. Older and larger households are more likely to become impoverished. According to Lekobane and Seleka (2017), family size, dependency ratio, and household age are positively associated with poverty. Households with working heads and higher educational levels are less likely to be impoverished. Households that have never married and are widowed, as well as those who live in rural areas, are more likely to be impoverished in Botswana. In Punjab, male-headed households, married households, family size, self-employment, and government work vs. wage employment all increase the likelihood of falling into poverty, while educational attainment decreases it (Iqbal et al., 2020). According to Shah et al. (2020), household size, dependency ratio, gender, and the household head's age all have a substantial impact on poverty status. Higher education reduces the likelihood of poverty, whereas a higher dependency ratio increases it. According to Sekhampu (2013), employment status, the age of the head of household, and household size are important predictors of poverty. The age and work status of the head of household lower the likelihood of poverty; however, larger households were associated with a higher likelihood of poverty. A high dependency ratio, as well as household engagement in firewood-selling activities, enhanced the chance of poverty.

To investigate the link between livelihood strategy and poverty, Barati et al. (2021) examined the multidimensional poverty index in rural Iran. The study employed the MPI index and the Fuzzy method. Poverty is influenced by a variety of factors, including household condition, household education, family size, family strategy, distance from the center, and access to natural resources. Furthermore, larger homes were more likely to be poor than smaller ones. The findings also revealed that poverty in rural livelihoods rose as a result of reliance on the agriculture industry and unemployment.

Gautam et al. (2021) investigated the internal link between poverty and non-climatic variation in rural farm-based families in Nepal's Gabdki Province. A sample of 300 from three separate groups was obtained. The Binary Probit Regression Approach was employed in this work to use the determinants of poverty shocks. Large household size, Dalit ethnicity, and farm households are characterized as impoverished. Furthermore, the study suggests that the shocks impacted households that rely on forestry, borrowing, and farming. Pathak et al. (2021) investigated the link between multidimensional poverty and TB in India. They used data from the fourth round of the National Family Health Survey for the fiscal year 2015-2016. The survey collected 628,900 samples. Its findings revealed a substantial relationship between multidimensional poverty and tuberculosis, but not between multidimensional non-poverty and non-tuberculosis.

Jaiyeola and Bayat (2020) examined income poverty trends in Nigeria using household survey evidence. Their analysis is relevant to discussions of persistent deprivation, although its measurement approach and time period differ from those used in the present study. Similarly, Eyasu (2020) investigated rural poverty in north-western Ethiopia and identified household size and non-farm income among the associated characteristics. These studies indicate that household composition and access to livelihoods warrant consideration in poverty analysis. However, observed associations across countries should not be assumed to have identical magnitudes or policy implications.

Mohamoud and Bulut (2020) studied household poverty in Somalia using a Logit specification. Their work considered household composition and livelihood-related conditions, including access to electricity and involvement in agricultural and other activities. In addition, the study illustrates the use of a binary-response framework to examine poverty status. However, the reported correlates should be understood within the study's own data, measures, and national context rather than transferred directly to Pakistan.

Evidence from Sindh and other parts of Pakistan highlights the importance of educational opportunities, assets, and local living conditions for household poverty. Guriro et al. (2019) discuss educational and poverty-reduction challenges in Sindh, whereas Waheed et al. (2020) examine multidimensional urban poverty in Lahore. Therefore, these studies provide complementary,

rather than identical, regional perspectives. In addition, Nawaz and Iqbal (2016) analyze the spatial distribution of education-related poverty across districts in Pakistan. Taken together, the studies suggest that household poverty is connected to both individual resources and geographical disadvantage. However, findings about education should be linked to the specific indicator used, because literacy, attainment, and multidimensional education deprivation are not interchangeable measures.

Khurram and Hassan (2019) investigated rural poverty in Pakistan and reported associations involving family size, characteristics of household heads, land ownership, livestock, and physical assets. Their findings indicate that household composition and access to productive resources are relevant considerations in explaining deprivation. Similarly, regional differences in gender-related poverty may reflect employment opportunities, household structure, and economic assets. However, comparisons between male- and female-headed households depend on the measures and controls included in each study. Therefore, the present analysis treats the sex of the household head as an explanatory indicator rather than assuming a uniform gender effect in advance.

Research on household poverty also highlights the importance of livelihood opportunities and access to productive activities. Farooq and Ahmad (2020) examine economic growth and rural poverty in Pakistan, while Rahman et al. (2020) analyze the circumstances of waste workers in Dhaka. Although these studies focus on different populations and economic sectors, they extend the discussion beyond demographic characteristics to the income-generating activities available to households. Similarly, their findings suggest that livelihood opportunities and local economic conditions deserve attention alongside education and family composition. However, country-specific economic structures should be considered before transferring conclusions across settings.

Furthermore, increasing education levels and improving adolescents' skills and training are among the prospects for reducing poverty. Idrees (2017) investigated poverty in the urban and rural regions of Islamabad's capital territory and each province. The research measures poverty using three distinct methods: headcount ratio, poverty gap, and squared poverty gap. Furthermore, except for the capital area of Islamabad, the data demonstrate that urban poverty is lower than rural poverty in all regions. Saleem and Khan (2017) researched the poverty ratios in four Pakistani provinces, as well as urban and rural regions. According to the study's findings, multidimensional poverty was much higher in Pakistan's rural regions than in its urban regions during the five time periods studied. Memon et al. (2015) examined the rural poverty rate in Tando Allahyar district of Sindh province, Pakistan. The findings showed that the rural areas studied rely on traditional agriculture and face inadequate infrastructure, illiteracy, and a lack of basic requirements, which hinder access to better income sources and contribute to regional poverty. Trani et al. (2016) investigated multidimensional poverty in Afghanistan by identifying impoverished persons with disabilities. According to Revandar and Minuwanthi (2020), many characteristics of poverty and income contribute to the association between the age of the head of household and poverty in Sri Lanka. They show an inverse relationship between the age of the family head, low income, and multi-layered poverty using HIES data from 2016. Furthermore, the study found that the likelihood of multi-layered poverty increases from 68.18 to 69.23 years and then declines. According to Garza et al. (2021), Mexico has a high proportion of poverty among families with multiple members and households headed by women or people who speak the original language. Additionally, household age is negatively associated with poverty, whereas family size is positively associated.

In Pakistan, Arshed et al. (2017) investigated the structural causes of poverty. The findings showed that all the explanatory factors—such as education, pay, work status, age, technical competence, etc.—are positively associated with the outcome variable. Mahmood et al. (2019) compared Pakistan's subjective and objective poverty levels. The researcher used data from the Pakistan Panel Household Survey (PPHS) from 2010, which surveyed 4,141 households. The results showed that several factors influenced the comparison between subjective non-poor and objective poor in the analyzed sample. For example, physical security, education, family size, and homeownership have a substantial direct relationship to reducing poverty relative to total non-poor, and the household also falls below the subjective poverty threshold. Sarwar et al. (2019) examined the many forms of

poverty and its causes in Pakistan. The results indicated that paid employment, household size, area, spouse, and job status all significantly and favorably affect poverty, whereas household head age, education, income, assets, spouse education, and spouse age all significantly and adversely affect poverty. Khan et al. (2020) investigated how transfer payments affected poverty across all provinces. According to the study's findings, Punjab and KP experienced less poverty as a result of the transfer payments. On the other hand, transfer payments have a beneficial effect on poverty levels in Balochistan and Sindh. Ahmad (2021) investigated how agriculture and remittances from abroad may help Pakistan's rural poor. In his opinion, agriculture is more effective at reducing rural poverty in the near term, while international remittances have a favorable long-term impact. Farooq and Ahmad (2020) analyzed rural poverty and economic growth in Pakistan, using data from three separate time periods: 2001-2004, 2001-2010, and 2005-2010. Furthermore, the findings suggest that livestock and animal ownership have a substantial and indirect association with poverty. Land ownership has a positive and substantial association with poverty. Cheema and Nadeem (2020) investigate poverty and its "basic correlates" in four provinces of Pakistan. The results show that poverty is lower in cities than in rural regions. According to the provincial poverty research, poverty is highest in Balochistan and lowest in Punjab. Furthermore, remittances (domestic and foreign), education (particularly for females in rural areas), social benefits (pension and other financial benefits), and ownership of property, computers, and livestock are important factors influencing poverty, whereas household size, dependency ratio, and unemployment have a negative impact. Gul et al. (2020) investigated the association between deprivation and income inequality in Bannu, Khyber-Pakhtunkhwa, Pakistan. The findings show that unemployment, poor socioeconomic conditions, a lack of educational opportunities, and a lack of access to healthcare services are the main causes of income disparity and poverty in the chosen location. Shaikh et al. (2020) investigated the impact of COVID-19 on poverty in Pakistan. They gathered information from 500 people in five districts: Shikarpur, Larkana, Sukkur, Kambershahdadkot, and Jacobabad.

3. Theoretical Framework

Classical explanations of poverty have sometimes emphasized individual circumstances and choices; however, structural perspectives highlight unequal opportunities, social exclusion, and constraints on access to resources (Bradshaw, 2007; Teitz & Chapple, 1998). Economic measures of poverty commonly focus on income or consumption, whereas a broader welfare perspective also considers education, nutrition, health, life expectancy, and access to essential services (Wagle, 2006; World Bank, 2009). Similarly, the World Bank's earlier international extreme-poverty threshold of $1.90 per person per day provides the monetary benchmark discussed in this study (World Bank, 2018). These perspectives are complementary rather than interchangeable: monetary poverty is the empirical outcome examined here, while household characteristics and functional limitations describe circumstances that may be associated with that outcome. In Pakistan, persistent differences in household resources, labor-market opportunities, and access to services provide a relevant context for examining such associations at the household level. However, interpreting the results requires recognition that poverty is not fully represented by any single monetary measure.

The study examines poverty in relation to household-head age, literacy, sex, and marital status; household dependency; urban or rural residence; province; and selected functional limitations. Based on the literature reviewed, education and access to economic opportunities may be associated with a lower probability of household poverty, whereas a higher dependency burden and disability-related barriers may be associated with a higher probability (Lekobane & Seleka, 2017; Majeed & Malik, 2015; Rosano et al., 2009). However, the directions and magnitudes of these associations must be evaluated empirically, not assumed. The analysis uses data from the Pakistan Social and Living Standards Measurement (PSLM) 2019–2020 survey, collected by the Pakistan Bureau of Statistics. The survey provides household-level information for examining differences in poverty status across demographic and geographical groups.

4. Methodology and Data

The Pakistan Bureau of Statistics (PBS) employed a two-stage stratified random sampling design for the Pakistan Social and Living Standards Measurement (PSLM) survey. The survey covered rural and urban areas of Khyber Pakhtunkhwa, Punjab, Balochistan, Sindh, Islamabad, Gilgit-Baltistan, and Azad Jammu and Kashmir. The preceding 2018–2019 survey was reported to comprise approximately 5,300 enumeration blocks, covering roughly 80,000 households, with each block containing approximately 200–250 dwellings. The 2019–2020 survey framework was reported to comprise approximately 6,500 blocks and cover approximately 195,000 households. However, 607 blocks were reportedly excluded because of COVID-19-related disruption, security concerns, and restrictions affecting military areas. These figures describe the survey framework rather than necessarily the complete-case sample used in the regressions. The study classifies poverty using a monetary threshold. Shah et al. (2020) provide related evidence on poverty measurement, and the source manuscript reports the Planning Commission of Pakistan's 2015–2016 benchmark as US$28.91 per person per month at an exchange rate of PKR 104 per US dollar. The manuscript also refers to the World Bank's historical international extreme-poverty threshold of US$1.90 per person per day (World Bank, 2018). For its own classification, the study converts US$1.90 into approximately PKR 303 using a stated exchange rate of PKR 159.4 per US dollar. However, international poverty thresholds are conventionally specified in purchasing-power-parity terms, and a market exchange-rate conversion is not equivalent to a PPP conversion. Therefore, the reported classification and the descriptive poverty share of approximately 66% should be interpreted as results under the manuscript's operational threshold, rather than as a verified official national extreme-poverty rate. In addition, the poverty measure and the effective survey sample should be made explicit when interpreting the regression results.

Following the household-level approach discussed by Idrees (2017) and Khurram and Hassan (2019), the dependent variable is a binary indicator of poverty. Specifically, poverty is coded 1 when the household falls below the study's stated threshold and 0 when the household is classified as non-poor. The manuscript operationalizes this threshold as income below US$1.90, or approximately PKR 303, per person per day; the non-poor category is defined as income exceeding this threshold. However, this conversion is the study's stated operational definition and should not be confused with a purchasing-power-parity-adjusted poverty line. Similarly, interpret the units and household-to-person conversion consistently. This poverty indicator is used as the dependent variable in both binary-response models, linking the analysis to Sustainable Development Goal 1 on ending poverty.

Age is considered a potentially nonlinear correlate of household poverty. The study measures the household head’s age in completed years, as recorded in PSLM 2019–2020, and includes both age and age squared in the regression specifications. This approach allows the association with poverty to change across the age distribution. For example, younger household heads may face limited labor-market experience, whereas older households may encounter different employment, health, and dependency circumstances. However, the direction and location of any turning point must be established from the estimated coefficients; they cannot be inferred solely from a general life-cycle argument. Therefore, age is retained as a continuous explanatory variable, and its square is included to capture potential nonlinearity.

Education is central to Sustainable Development Goal 4 and is also a relevant household-level correlate of poverty. The PSLM 2019–2020 survey reports literacy status, which this study operationalizes as a binary measure for the household head. The indicator takes the value 1 when the household head is literate and 0 when the household head is illiterate. However, literacy should not be interpreted as a complete measure of educational attainment, schooling quality, or employment-related skills. Accordingly, the empirical results describe the association between the literacy indicator and poverty status within the specified model.

Marital status is included to capture an additional household-head characteristic potentially associated with poverty. The analysis distinguishes married and unmarried household heads through a binary indicator, coded 1 for married household heads and 0 otherwise. Differences in household resources, family composition, and care responsibilities may be relevant to this

comparison. However, marital status should not be assumed to affect poverty in the same manner across gender and age groups. Therefore, the coefficient is interpreted as a conditional association with household poverty, rather than an independently established effect of marriage.

The sex of the household head is included as a separate explanatory variable. Specifically, a binary indicator takes the value 1 for a male household head and 0 otherwise, thereby using female-headed households as the comparison category in the reported sample. This definition permits the study to examine differences in observed poverty status after accounting for the other variables in the specification. However, the resulting estimates should not be generalized to all men and women, because the indicator refers to household headship and may reflect differences in household composition or economic circumstances.

The dependency ratio (DR) is used as a continuous measure of household composition. Dependent household members are defined as those younger than 15 or older than 64, whereas the reference working-age group comprises those aged 15–64. Accordingly, the ratio is calculated by dividing the number of dependent members by the number of working-age members. This measure approximates the household's demographic dependency burden; however, it does not directly measure employment, unpaid care, or the income contributed by any household member.

Dependency ratio (DR) = (number of members aged below 15 years + number aged above 64 years) / number of members aged 15–64 years.

The PSLM 2019–2020 dataset also permits comparisons by residence and province. Urban residence is coded 1 and rural residence 0. The dataset includes three provincial indicators for Khyber Pakhtunkhwa, Punjab, and Sindh, with Balochistan serving as the reported reference province. Therefore, interpret the provincial coefficients relative to Balochistan, and do not treat them as an independent ranking of provincial poverty rates. In addition, the survey contains questions on functional limitations, including difficulty seeing, hearing, walking, remembering or concentrating, washing or dressing, and communicating. The manuscript also identifies an indicator for any form of disability. These categories broaden the scope of household-level poverty analysis by highlighting disability-related disadvantage. However, individual limitation indicators may overlap, and their simultaneous inclusion should be considered when interpreting the estimates.

Linear regression is frequently used in economic and social research; however, a binary dependent variable limits a conventional linear probability specification. In the present study, poverty is coded as 1 for a poor household and 0 for a non-poor household. Therefore, a binary Logit model is estimated to examine the association between the selected household characteristics and the probability of being classified as poor. The Logit specification constrains predicted probabilities to the interval between 0 and 1. In addition, a Probit model is estimated as an alternative binary-response specification to compare the direction and statistical significance of the associations. The following expression represents the Logistic probability model used in the analysis.

$$y_i= E(p=1 | X_i) = 1/(1+e^{(- (\beta o+\sum 〚\beta ixi)〛)) 1}$$

Here, Y denotes the probability that household i is classified as poor, conditional on the explanatory variables X_i. The value P = 1 identifies a poor household, whereas P = 0 identifies a non-poor household. The intercept is β_0, the coefficients on the explanatory variables are β, and e denotes the base of the natural logarithm. Accordingly, the coefficients describe changes in the log-odds of poverty; they should not be interpreted directly as percentage-point changes in probability without the corresponding marginal-effects calculation. In the current study, we also used the Probit Regression model because the dependent variable is Binary/Dichotomous in nature. We can explain Probit regression using an equation.

$$p^*= a_1+a_2 X1+a_1 X2\ldots\ldots\ldots\ldots a_K XK_(i)+e_i 2$$

In this expression, p* denotes the latent propensity underlying the observed binary poverty indicator, while X represents the explanatory variables. The Probit specification links the latent index to the observed probability of poverty through the standard normal cumulative distribution

function. Therefore, comparisons between the Logit and Probit results should focus on substantive interpretation and corresponding marginal effects rather than raw coefficients alone.

Marginal effects are calculated after estimating the binary-response models. They express the change in predicted probability associated with a change in an explanatory variable, holding the relevant specification and evaluation method constant. For a continuous explanatory variable, the marginal effect is a derivative of the predicted probability with respect to that variable. For a binary explanatory variable, a discrete change from 0 to 1 is generally more appropriate. Consequently, marginal effects should be distinguished from regression coefficients and reported with their units, standard errors, and statistical uncertainty where available.

$$dY/dX \quad 3$$

In Equation (3), Y represents the predicted probability of poverty, and X denotes an explanatory variable. A positive marginal effect indicates a higher predicted probability of poverty as the explanatory variable increases, whereas a negative effect indicates a lower predicted probability. However, the interpretation depends on the variable's measurement scale and whether it is continuous or binary. Accordingly, numerical statements about the probability of poverty should be based on the estimated marginal effects rather than solely on the signs of regression coefficients. The following model specifies the household-level determinants examined in this study.

$$Pi=a_0+AgeHHa_1+Age2HHa_2+HHlitratea_3+MaleHHa_4+HHMarrieda_5+URBANa_6+DRa_7+KPa_8+PNJa_9+SNDa_10+D1a_11+D2a_12+D3a_13+D4a_14+D5a_15+D6a_16+aD7a_17+e \quad 4$$

In the above model, P represents the dependent variable (poverty), and i represents ("1" and "0")

Pi= 1 if household i is poor

Pi= 0: household i is non-poor

AgeHH, complete years of the household head. The age is a continuous variable in the study. Age2HH taking square on age, HHL, represent household head education status, literate = "1" and "0" otherwise, MaleHH is represent male household head, (male = 1 and 0, otherwise), HHMarried is the household head married (married=1 and otherwise 0), URBAN is the household from urban area, (urban=1 and 0 otherwise), DP is number of dependent in household, KP household belong to KP, PNJ household belong to Punjab, SND household belong to Sindh and household from Balochistan is base category. D1 is seeing disability, D2 is hearing disability, D3 is walking disability, D4 is remembering disability, D5 is washing disability, D6 is language disability, D7 is any kind of disability, and e represents the error term; α0 is the intercept, and αi…n are the slope parameters.

5. Analysis and Results

Table 2 reports descriptive statistics for the variables included in the study. The narrative initially describes an analytical sample of 160,330 observations, whereas the table reports 160,727 observations for several variables; consequently, the source material does not resolve the difference between the stated sample counts. The table reports a mean poverty indicator of approximately 0.660, which indicates that about 66% of observations fall below the study's operational poverty threshold. However, this percentage should not be labeled an official population poverty rate without verification of the threshold, denominator, and applicable survey weights. Household-head age ranges from 14 to 99 years, with a mean of approximately 46 years. The reported proportion of literate household heads is about 63.9%; approximately 82.4% of household heads are male, and 87.5% are married. Urban households represent approximately 31.1% of observations. In addition, the study reports provincial and disability-related indicators, including difficulties related to vision, hearing, walking, dressing or washing, communication, and memory. These descriptive distributions establish the sample context for the subsequent Logit and Probit results. Similarly, related work on subjective and objective poverty in Pakistan highlights the importance of clearly specifying how deprivation is measured (Mahmood et al., 2019).

Marginal effects are reported alongside the binary Logit results to describe changes in the predicted probability of poverty associated with the explanatory variables. The dependent indicator takes the value 1 for poor households and 0 for non-poor households. Table 7 presents the Logit estimates and associated uncertainty measures. However, a coefficient's sign indicates the direction of its association with the model's latent index or log-odds; it does not, by itself, indicate a percentage-point change in probability. Therefore, interpret effect magnitudes using the corresponding reported marginal effects, paying attention to each variable's measurement scale.

The Logit model identifies household characteristics associated with the probability of poverty, with the reported estimates presented in Table 7. The model's reported log-likelihood is −91,220.256. However, the numerical value of the log-likelihood cannot, by itself, demonstrate that the specification fits well: comparisons require an appropriate benchmark, such as another model fitted to the same observations, or additional measures of predictive performance. Therefore, interpret the estimates primarily through the reported coefficient signs, marginal effects, and associated measures of statistical uncertainty.

The reported Logit estimates identify statistically significant associations involving household-head age and literacy, sex and marital status, dependency ratio, urban residence, province, and several functional limitations. The source narrative describes these relationships as statistically significant at the 1% level. However, significance should be determined from the table's reported standard errors and significance markers rather than from the direction or numerical size of coefficients. In addition, the practical importance of an association is distinct from its statistical significance, particularly in a large sample.

The estimated coefficient for household-head age is positive, while the coefficient for age squared is negative. This combination indicates a nonlinear association in the model's fitted index and is consistent with an inverted-U specification, rather than a U-shaped coefficient pattern. The manuscript reports a 2% change associated with age and a −0.02% change associated with age squared; however, these quantities should be checked against the marginal-effects output because the effect of age in a quadratic model varies with age. Majeed and Malik (2015) discuss related evidence on household poverty and age. In addition, calculate a turning point from the relevant coefficient estimates before asserting that poverty risk necessarily rises or falls after a particular age. Thus, the nonlinear age specification is retained, while its precise probability interpretation remains dependent on the reported estimates and their units.

Household-head literacy is an important correlate of poverty in the reported results. The manuscript describes a reduction of approximately 16 percentage points in the predicted probability of poverty for literate household heads, relative to those classified as illiterate, although the precise unit of this estimate should be checked against the marginal-effects table. This direction is consistent with literature linking educational resources to household welfare (Majeed & Malik, 2015; Nawaz & Iqbal, 2016). Education may strengthen access to economic opportunities and earning capacity. However, the estimated relationship remains an association between the binary literacy indicator and poverty status, rather than evidence that literacy alone necessarily allows households to escape poverty. Therefore, policy interpretation should consider educational quality, labor-market access, and local circumstances.

The analysis includes the household head's sex and marital status as separate explanatory variables. The manuscript reports an approximately 49% higher probability of poverty for male-headed than for female-headed households in its discussion of the Logit results, while also describing the sign of the male-head coefficient as negative. However, these statements are inconsistent and must be reconciled against the regression table and the marginal-effects estimates. Evidence from Majeed and Malik (2015) provides a relevant comparison for household-head characteristics. Therefore, the substantive conclusion should rest on the correctly matched coefficient, reference category, and marginal effect, rather than on a contradictory directional statement.

Marital status is also included in the Logit specification. According to the manuscript's reported marginal-effects interpretation, a household with a married head has an approximately 6-

percentage-point lower probability of poverty than a household with an unmarried head, conditional on the other covariates. This comparison is consistent with the broader interest in family structure in household-poverty research (Majeed & Malik, 2015). However, the result does not imply that marriage itself reduces poverty, as economic circumstances and household composition may influence both marital status and poverty. Therefore, the finding should be regarded as a conditional association within the cross-sectional data.

Urban residence is reported to be negatively associated with the predicted probability of poverty. The manuscript indicates that urban households have an estimated probability of poverty approximately 9 percentage points lower than rural households, conditional on the specified characteristics. This pattern is consistent with Pakistan-focused work identifying substantial rural–urban differences in poverty and access to resources (Cheema & Nadeem, 2020; Idrees, 2017). However, the contrast may reflect multiple differences in employment opportunities, infrastructure, public services, and living costs. Similarly, these relationships may vary between provinces and household groups. Accordingly, the result should be interpreted as a geographical association rather than a causal benefit of urban residence.

Household dependency is positively associated with poverty in the reported Logit results. The manuscript describes an approximately 29-percentage-point increase in the predicted probability of poverty for a one-unit increase in the dependency ratio. However, because the ratio is continuous, the interpretation depends on its precise scaling and the marginal-effects evaluation procedure used. Related evidence has identified household dependency as a relevant correlate of deprivation (Lekobane & Seleka, 2017; Shah et al., 2020). Therefore, the result suggests that the number of dependants relative to working-age members is an important dimension of household vulnerability, although it does not establish the effect of a specific policy intervention.

Relative to Balochistan, the reference province, the reported Logit comparisons indicate a lower predicted probability of poverty for households in Khyber Pakhtunkhwa and Punjab and a higher predicted probability for those in Sindh. The source narrative describes differences of approximately −13, −3, and +7 percentage points, respectively. However, these are conditional provincial contrasts with Balochistan, not direct estimates of each province's poverty incidence. The results should therefore be distinguished from the descriptive provincial percentages cited in the introduction. In addition, differences in household characteristics and local economic conditions may contribute to the estimated associations.

The manuscript also reports positive associations between poverty and several forms of functional limitation. The Logit narrative describes increases in predicted poverty probability of approximately 3 percentage points for difficulties with seeing, hearing, walking, or remembering and concentrating; 5 points for washing and dressing; 6 points for communication; and 4 points for the indicator representing any disability. However, check the exact marginal effects and overlap between these indicators against Table 7. Previous work on disability and deprivation provides a relevant comparative context (Rosano et al., 2009; Trani et al., 2016). In addition, barriers to accessible education, employment, and healthcare may accompany disability-related poverty. These observations support policy attention to inclusion but do not establish a causal effect from the cross-sectional estimates.

Marginal effects were also calculated after estimating the Probit model, with the corresponding results presented in Table 8. As in the Logit specification, the explanatory variables include household-head age and its square, literacy, sex, marital status, dependency ratio, geographical location, and functional limitations. The discussion reports positive associations for dependency and selected disability indicators and negative associations for literacy, marital status, and urban residence. However, the original narrative gives conflicting directions for the male-head variable. Accordingly, interpret the direction of that association from the reported estimates rather than infer it from the conflicting prose. In addition, compare the findings for each province with the stated reference province, Balochistan. The estimated associations represent conditional relationships in the sampled households, not evidence that the observed characteristics cause poverty.

The reported Probit specification provides an alternative binary-response model for the same poverty outcome. As presented in Table 8, the study discusses associations involving household-head age, literacy, sex, marital status, dependency ratio, disability-related indicators, urban residence, and province. The stated log-likelihood of the Probit model is −91,235.977. However, a more negative log-likelihood does not indicate a better-fitting model; valid model comparisons require the same sample and an appropriate comparison criterion. The substantive direction of the estimates should be evaluated in conjunction with marginal effects and uncertainty measures. Therefore, the Probit results are most useful here as a check on whether the broad patterns observed in the Logit specification remain similar under a different link function.

Table 8 presents the reported Probit marginal effects for the functional-limitation indicators. The source narrative lists estimated increases in poverty probability of approximately 3, 3, 3, 4, 5, 6, and 3 percentage points for seeing, hearing, walking, remembering or concentrating, washing or dressing, communication, and any disability, respectively, compared with households without the corresponding reported limitation. These magnitudes should be interpreted with reference to the original variable coding and the estimated effects in the table. In addition, because several limitation categories may be observed in the same household, the estimates should not automatically be combined into a single cumulative probability change. The positive associations are nevertheless consistent with broader concerns about disability-related economic vulnerability (Rosano et al., 2009; Trani et al., 2016).

Household-head age is another potentially important correlate of poverty. In the Probit specification, the reported coefficient for age is positive, and the coefficient for age squared is negative. Therefore, these coefficient signs imply an inverted-U relationship in the latent index, rather than the U-shaped relationship stated in the original narrative. The manuscript also reports an 8% change for age and a −0.023% change for age squared. However, the net marginal effect of age depends on both terms and on the point at which the effect is evaluated. In addition, the squared-age term is not a separate one-year increase in age. Consequently, precisely describing the turning point and the size of the probability change requires examining the estimated coefficients and marginal-effects calculations. The nonlinear specification is retained because it remains relevant to the study's original objective.

The Probit narrative reports a higher predicted probability of poverty for male-headed households, with an approximate 45-percentage-point difference relative to the reference category. However, the direction and magnitude must be read alongside the corresponding regression coefficient and marginal-effects column because the original manuscript contains inconsistent descriptions of this gender-related result. The reported literacy association is negative, with an estimated difference of approximately 16 percentage points between literate and illiterate household heads. Similarly, the analysis reports a lower probability of poverty for married household heads (approximately 6 points) and urban households (approximately 9 points). Compared with Balochistan, the Probit narrative describes lower estimated poverty probabilities for Khyber Pakhtunkhwa (approximately 12 points) and Punjab (approximately 3 points), but a higher probability for Sindh (approximately 8 points). These figures are the source manuscript's reported interpretations rather than independently recalculated effects. Relevant comparative research includes studies of household welfare, regional poverty, family composition, and disability-related deprivation (Adjasi & Osei, 2007; Deyshappriya & Minuwanthi, 2020; Lekobane & Seleka, 2017; Majeed & Malik, 2015; Rosano et al., 2009). Therefore, any final quantitative interpretation should preserve the relevant reference categories and the percentage-point units of the marginal effects.

6. Discussion and Policy Relevance

The results highlight the importance of considering household poverty in relation to educational resources, dependency, disability-related barriers, and place of residence. The negative association reported for household-head literacy is consistent with the poverty literature's emphasis on human capital (Majeed & Malik, 2015; Nawaz & Iqbal, 2016). However, literacy is not equivalent to years of schooling, educational quality, or access to well-paid employment. Therefore, the result should be interpreted as evidence that literacy status and household poverty are related within the

estimated model. Similarly, the positive association between household dependency and poverty suggests that household composition deserves attention alongside labour-market opportunities and social protection (Lekobane & Seleka, 2017; Shah et al., 2020).

The disability indicators provide a second important dimension of the analysis. Rather than treating functional limitations solely as an individual characteristic, the household perspective allows consideration of their association with economic disadvantage. Previous studies have similarly connected disability with broader deprivation and constraints on capabilities (Rosano et al., 2009; Trani et al., 2016). However, the survey results do not establish whether disability preceded poverty or whether poverty contributed to disability-related vulnerability. In addition, the reported estimates should not be interpreted as the independent causal effect of each type of functional limitation. The findings nevertheless point to the relevance of inclusive education, accessible services, rehabilitation support, and employment participation when designing poverty-reduction policies.

Geographical differences also warrant careful interpretation. The comparison between rural and urban households is consistent with evidence that poverty-related conditions vary across location and access to resources (Cheema & Nadeem, 2020; Idrees, 2017). Similarly, provincial indicators may capture a mix of labor-market conditions, infrastructure, social services, and household characteristics that the model does not measure directly. Therefore, interpret the provincial regression coefficients relative to Balochistan, the stated reference category, rather than as stand-alone rankings of provincial poverty rates. These distinctions make the findings more useful for identifying research priorities and for developing locally sensitive policy questions.

Several limitations should be recognized. First, the results depend on the poverty-line definition and its currency or purchasing-power conversion; the reported use of the historical international $1.90 threshold requires verification of the appropriate purchasing-power-parity basis. Second, the source manuscript reports different sample counts in the narrative and descriptive table, and the analytical sample should be specified consistently. Third, document the stratified survey design, observation weights, and uncertainty estimates when national inference is intended. Fourth, cross-sectional data cannot establish causal direction, while some covariates may be jointly determined with household poverty. Finally, the opposite signs of age and age squared require a correctly calculated turning point, and statements concerning gender should be checked against the corresponding regression outputs. Future research could assess sensitivity to defensible poverty thresholds, compare survey-weighted estimates, and investigate heterogeneity across provinces and functional-limitation groups. These are proposed extensions rather than analyses claimed to have been performed in this study.

7 Conclusion and Recommendations

The study examines household-level factors associated with poverty in Pakistan using the Pakistan Social and Living Standards Measurement (PSLM) 2019–2020 survey. Because the dependent variable distinguishes poor from non-poor households, Logit and Probit specifications are used to analyze the selected characteristics. The descriptive analysis reports a poverty share of about 66% in the analytical sample, an average household-head age of about 46 years, an urban-residence share of 31%, and a household-head literacy share of about 63%. These figures describe the sample as reported in the study and should not be presented as nationally representative population rates without validating the poverty threshold and survey weighting. The regression discussion identifies associations involving the dependency ratio, functional limitations, household-head literacy and marital status, urban residence, and provincial location. In particular, the reported positive relationships involving several functional limitations point to the relevance of disability inclusion for understanding household disadvantage. Similarly, the reported negative association for urban residence suggests meaningful rural–urban differences in poverty-related circumstances. However, the direction of the age and gender results must be consistent with the model estimates, and provincial comparisons must retain the specified Balochistan reference category. The analysis therefore offers evidence on the coexistence of demographic, educational, geographical, and disability-related disadvantages within households. Its cross-sectional design supports statements of association but not definitive causal attribution. In addition, the findings highlight the need to

interpret poverty indicators in relation to the data source, the poverty threshold, and the characteristics of the households represented.

Policy responses to disability-related poverty should combine accessible public services, rehabilitation support, inclusive employment opportunities, and appropriately targeted social assistance. In addition, predictable support for households facing disability-related barriers may help reduce financial insecurity, although the effectiveness of particular programs must be assessed separately. Education and vocational training are similarly relevant because household-head literacy is negatively associated with poverty in the reported analysis (Majeed & Malik, 2015). Therefore, measures that expand access to affordable, inclusive education should be considered alongside efforts to improve rural infrastructure, health provision, and employment opportunities. The reported association between dependency and poverty also supports greater attention to household composition and the availability of working-age income, care services, and social protection. However, this association alone does not show that reducing household size would reduce poverty. Provincial differences further suggest that place-sensitive initiatives are preferable to uniform approaches that do not account for local circumstances (Cheema & Nadeem, 2020; Idrees, 2017). These priorities are relevant to SDG 1 on poverty reduction, SDG 4 on education, SDG 8 on decent work, and SDG 10 on reduced inequalities. Accordingly, future evaluations should assess whether inclusive policies improve household welfare among groups facing multiple disadvantages.

Ethical Statement: The study analyses secondary data from the Pakistan Social and Living Standards Measurement (PSLM) Survey 2019–2020.

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Appendix

Table 2: Descriptive Statistics

Variables	Obvs	Mean	Stdev	Min	Max
POVERTY	160,727	0.6601131	0.473672	0	1
HHAGE	160,727	46.25344	14.41445	14	99
HHAGE2	160,727	2346.869	1406.939	196	9801
HHLITRATE	160,727	0.6387267	0.4803739	0	1
HHMALE	160,727	0.823958	0.3808594	0	1
HHMARRIED	160,727	0.8751762	0.3305221	0	1
URBAN	160,727	0.3111798	0.4629776	0	1
DEP RATIO	160,727	0.4322795	0.2933109	0	6
KPK	160,727	0.1782463	0.3827212	0	1
PUNJAB	160,727	0.4960025	0.4999856	0	1
SINDH	160,727	0.2308946	0.4214065	0	1
BALOCH	160,727	0.0948565	0.2930175	0	1
D1	160,330	0.1443211	0.3514161	0	1
D2	160,330	0.1073224	0.3095237	0	1
D3	160,330	0.2376099	0.4256202	0	1
D4	160,330	0.114545	0.318473	0	1
D5	160,330	0.1097549	0.312585	0	1
D6	160,330	0.0802595	0.2716953	0	1
D7	160,330	0.3799913	0.4853858	0	1

Source: Calculated by author.

Table 3: Disabled poor and non-poor of Khyber Pakhtunkhwa

KPK	Disable poor and non-poor		
Disabilities	Total	Poor disable	Non poor disable
D1=Seen disability	4,014	2,280	1734
D2=Hearing disability	3,272	1,778	1494
D3=Walking disability	7,260	4,122	3138
D4=Remembering disability	3,584	2,052	1532
D5=Washing disability	3,115	1,749	1366
D6=Language disability	2,389	1,375	1323
D7=Any kind of disability	11,179	6,337	4839

Source: Calculated by the author

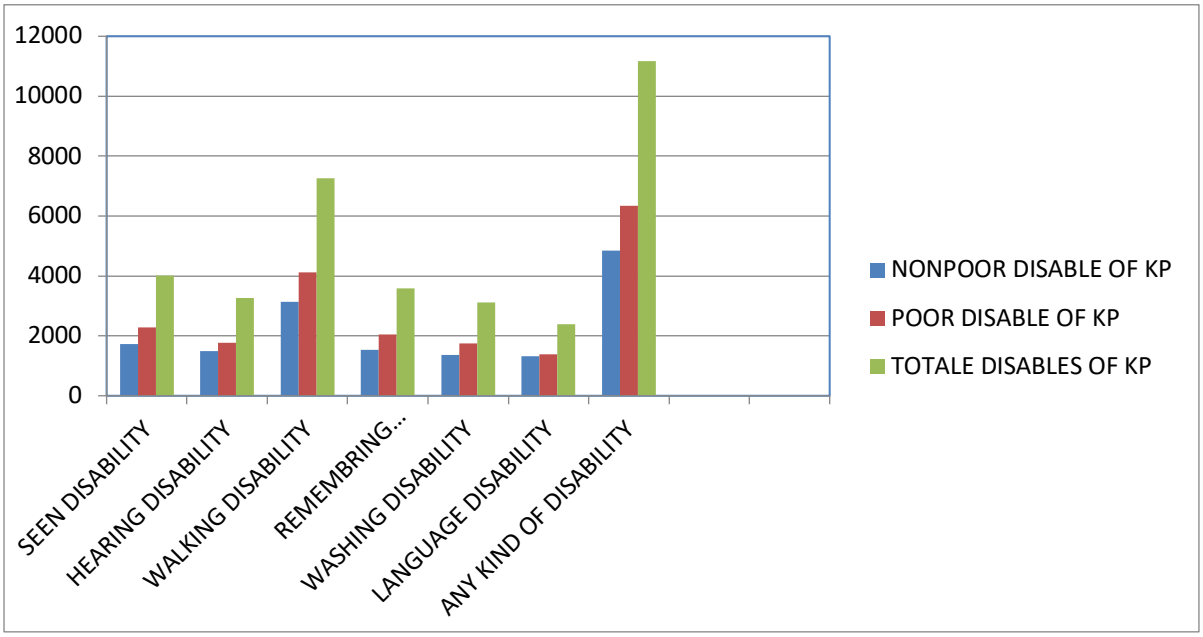


Figure 1: Descriptive Statistics of Disabled Poor and Non-Poor of KP

Table 4: Disabled Poor and Non-Poor of Punjab

Punjab	**Disable poor and non-poor**		
Disabilities	Total	Disabilities	Total
D1=seen disability	12282	7809	4473
D2=hearing disability	9196	6001	3195
D3=walking disability	19810	12454	7356
D4=remembering disability	9221	6146	3075
D5=washing disability	9030	6150	2880
D6=language disability	6466	4524	1942
D7=any kind of disability	32274	20471	11803

Source: Calculated by author

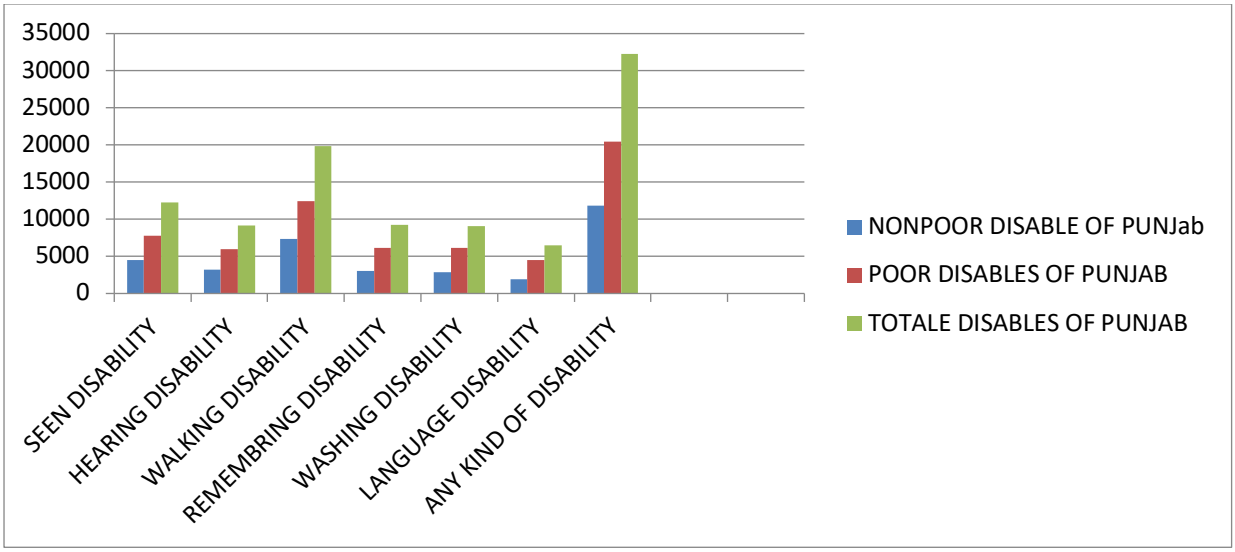


Figure 2: Descriptive Statistics of Poor Disable and Non-Poor Disable Punjab

Table 5: Descriptive Statistics of Disabled Poor and Disable Non-Poor of Sindh

Sindh	**Disable poor and non-poor**		
Disabilities	Total	Disabilities	Total
D1=Seen disability	5042	3570	1472
D2=Hearing disability	3398	2523	875
D3=Walking disability	7966	5844	2122
D4=Remembering disability	4092	3218	811

Sindh	Disable poor and non-poor		
D5=Washing disability	3902	3183	719
D6=Language disability	2934	2443	491
D7=Any kind of disability	12623	9300	3323

Source: Calculated by the author.

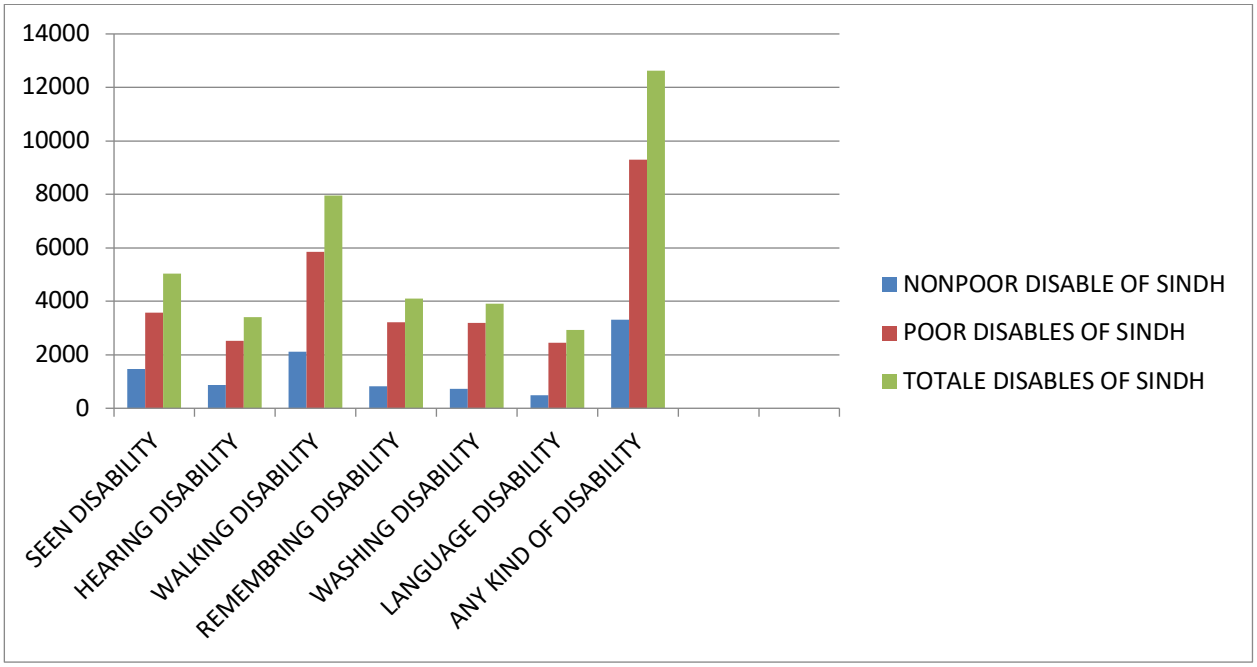


Figure 3: Descriptive Statistics of Disabled Poor and Non-Poor of Sindh

Table 6: Descriptive Statistics of Disabled Poor and Disabled Non-Poor of Baluchistan

Baluchistan		Disable poor and non-poor	
Disabilities	Total	Disabilities	Total
D1=seen disability	1801	1385	416
D2=hearing disability	1341	1043	298
D3=walking disability	3060	2385	675
D4=remembering disability	1468	1173	295
D5=washing disability	1550	1211	339
D6=language disability	1070	892	178
D7=any kind of disability	4851	3745	1106

Source: Calculated by the author.

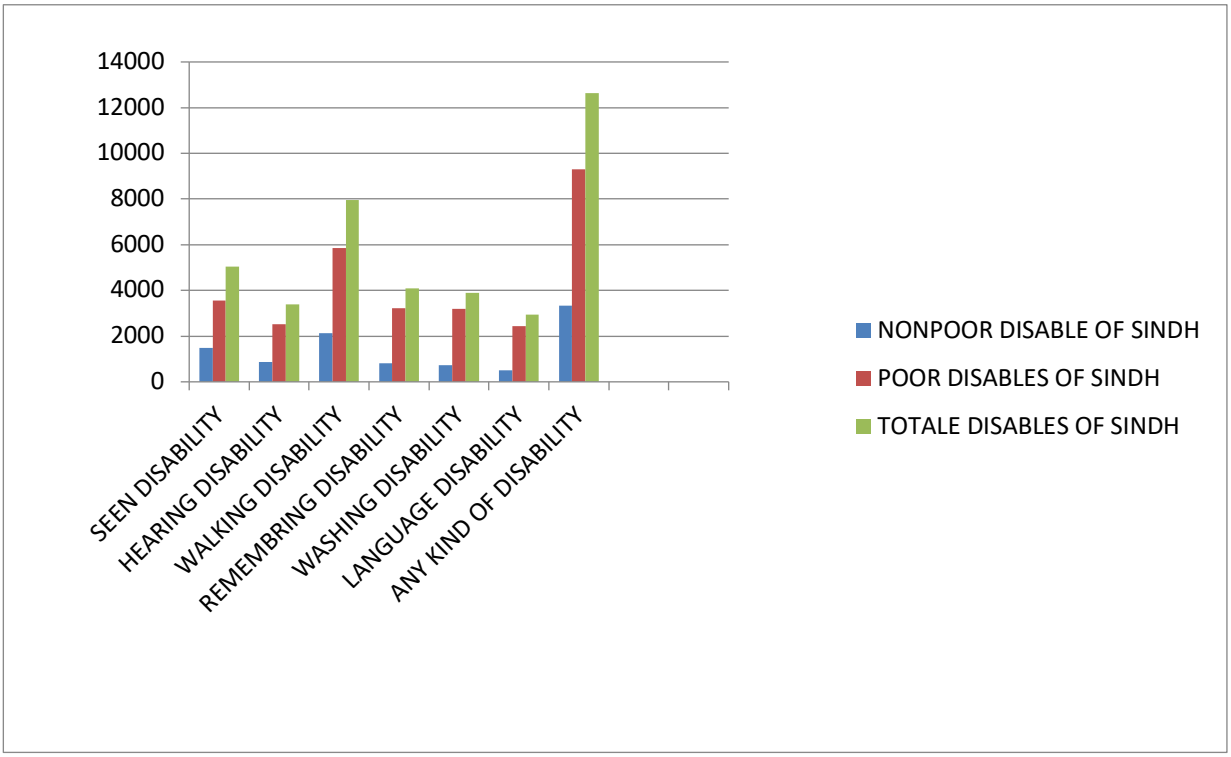


Figure 4: Descriptive Statistics of Disabled Poor and Non-Poor in Baluchistan

Table 7: Results of Logit Model

VR	Logit (1)	Logit (2)	Logit (3)	Logit (4)	Logit (5)	Logit (6)	Logit (7)
Age HHH	0.0188*** (0.00054)	0.01891*** (0.00054)	0.01897*** (0.00055)	0.01908*** (0.00055)	0.01899*** (0.00054)	0.0188*** (0.00054)	0.01866*** (0.00054)
Age2	-0.000234*** (0.00001)	-0.00024 (0.00001)	-0.00024*** (0.00001)	-0.00024 (0.00001)	-0.00024 (0.00001)	-0.00023*** (0.00001)	-0.00024 (0.00001)
HHLiterate	-0.1638*** (0.00254)	-0.1637*** (0.00254)	-0.1638*** (0.00254)	-0.1637*** (0.00254)	-0.1635*** (0.00254)	-0.1634*** (0.00254)	-0.1639*** (0.00254)
HHMale	0.4906*** (0.00416)	0.4905*** (0.00416)	0.4903**** (0.00416)	0.4905*** (0.00416)	0.4901*** (0.00416)	0.4904*** (0.00416)	0.4898*** (0.00416)
HHMarried	-0.0693*** (0.00434)	-0.0695*** (0.00434)	-0.0687*** (0.00434)	-0.0688*** (0.00434)	-0.0688*** (0.00434)	-0.0690*** (0.00434)	-0.0684*** (0.00435)
Urban	-0.0883*** (0.00293)	-0.0879*** (0.00293)	-0.0883*** (0.00293)	-0.0877*** (0.00293)	-0.0876*** (0.00295)	-0.0876*** (0.00293)	-0.08822*** (0.00293)
Dep ratio	0.2969*** (0.00449)	(0.2957)*** ((0.00449)	0.2960*** (0.00449)	0.2935*** (0.0045)	0.2933*** (0.0045)	0.2932*** (0.0045)	0.2971*** (0.00449)
Kpk	-0.1246*** (0.0056)	-0.1249*** (0.0056)	-0.1252*** (0.0056)	-0.1255*** (0.0056)	-0.1244*** (0.0056)	-0.1252*** (0.0056)	-0.1252*** (0.0056)
Punjab	-0.0326*** (0.00463)	-0.0327*** (0.00463)	-0.0326*** (0.00463)	-0.0327*** (.00463)	-0.0325*** (0.00463)	-0.0328*** (0.00463)	-0.0336*** (0.00463)
Sindh	0.0758*** (0.0048)	0.0760*** (0.00476)	0.0760*** (0.00476)	0.0756*** (0.00476)	0.0760*** (0.00476)	0.0756*** (0.00476)	0.0757*** (0.00476)
Disability1	0.0270*** (0.00347)						
Disability2		0.0314*** (0.00391)					
Disability3			0.0297*** (0.00296)				
Disability4				0.053*** (0.00374)			
Disability5					0.0512*** (0.00382)		
Disability6						0.0625*** (0.00432)	
Disability7							0.0347***

VR	Logit (1)	Logit (2)	Logit (3)	Logit (4)	Logit (5)	Logit (6)	Logit (7)
							(0.00269)
Observation	160,330	160,330	160,330	160,330	160,330	160,330	160,330
Pseudo-R2	0.1117	0.1117	0.2119	0.1123	0.1123	0.1124	0.1122
Log likelihood	-91220.256	-91201.815	-91158.31	-91166.963	-91154.974	-92030.114	-91169.416

Note: standard errors in parentheses. 2. ***, **, and * indicate the 1%, 5%, and 10% levels of significance.

Table 8: Results of Probit Model

VAR	Probi (1)	Probit (2)	Probit (3)	Probit (4)	Probit (5)	Probit (6)	Probit (7)
Age HHH	0.0184*** (0.00053)	0.0185*** (0.00053)	-0.01858*** (0.00053)	-0.0186*** (0.00053)	-0.0186*** (0.00053)	-0.0184*** (0.00053)	-0.0183*** (0.00053)
Age 2	-0.00023*** (0.00001)	-0.00023*** (0.00001)	-0.00023*** (0.00001)	-0.00023*** (0.00001)	-0.00023*** (0.00001)	-0.00023*** (0.00001)	-0.000223*** (0.00001)
HHLiterate	-0.1614*** (0.0025)	-0.1613*** (0.0025)	-0.1614*** (0.0025)	-0.1613*** (0.0025)	-0.1611*** (0.0025)	-0.1611*** (0.0025)	-0.1615*** (0.0025)
HHMale	0.4796*** (0.00424)	0.4796*** (0.00424)	0.4794*** (0.00424)	0.4796*** (0.00424)	0.4793*** (0.00424)	0.4796*** (0.00424)	0.4788*** (0.00424)
HHMarried	-0.0679*** (0.0043)	-0.0681*** (0.0043)	-0.0674*** (0.0043)	-0.0674*** (0.0043)	-0.0674*** (0.0043)	-0.0677*** (0.0043)	-0.0671*** (0.0043)
Urban	-0.0865*** (0.00287)	-0.0860*** (0.00287)	-0.0864*** (0.00287)	-0.0859*** (0.00287)	-0.0857*** (0.00287)	-0.0857*** (0.00287)	-0.0863*** (0.00287)
Dep ratio	0.0287*** (0.00434)	0.2862*** (0.00434)	0.2865*** (0.00434)	0.2840*** (0.00434)	0.2837*** (0.00434)	0.2837*** (0.00434)	0.2874*** (0.00434)
Kpk	-0.1220*** (0.00535)	-0.1223*** (0.00535)	-0.1228*** (0.00434)	-0.1229*** (0.00535)	-0.1218*** (0.0053)	-0.1226*** (0.0053)	-0.1233*** (0.0053)
Punjab	-0.0316*** (0.00449)	-0.0317*** (0.00449)	-0.0317*** (0.00449)	-0.0318*** (0.00449)	-0.0315*** (0.00449)	-0.0319*** (0.00449)	-0.0327*** (0.00449)
Sindh	0.0764*** (0.0067)	0.0766*** (0.0047)	0 .0765*** (0.00467)	0.0760*** (0.00467)	0.0766*** (0.00467)	0.0761*** (0.00467)	0.0762*** (0.00467)
Disability1	0.0266*** (0.00345)						
Disability2		0.0314*** (0.00388)					
Disability3			0 .0293*** (0.00294)				
Disability4				0.0452*** (0.00371)			
Disability5					0.0504*** (0.00378)		
Disability6						0.0620*** (0.00428)	
Disability7							0.0341*** (0.00266)
Observation	160,330	160,330	160,330	160,330	160,330	160,330	160,330
Pseudo R2	0.1116	0.1116	0.1118	0.1123	0.1123	0.1124	0.1122
Log likelihood	-91235.977	-91233.319	-91216.224	-91171.852	-91180.956	-91167.575	-91183.592

Note: standard errors in parentheses. 2. ***, **, and * indicate the 1%, 5%, and 10% levels of significance.