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KEYWORDS	ABSTRACT
Multiple dimension of energy poverty, PCA, energy access, spatial inequalities, one-way ANOVA, t-test,	Energy poverty is important to address its eradication. This paper deals with the multidimensionality of energy poverty and the spatial inequality of energy poverty in Pakistan using the latest cross-sectional data (2019 to 2020) from the PSLM survey. The multiple dimensions of energy poverty are calculated using a set of fifteen major indicators and weights assigned using the Principal Component Analysis technique. One of the most basic and fundamental necessities of a nation is access to clean and modern energy. The study investigates whether there is a spatial inequality in access to energy services in Pakistan. Inequities are analyzed both within and across the provinces of Pakistan. Approximately 155,988 entries make up the study dataset. Statistical techniques including one-way ANOVA and T-testing are used to inspect these inequities. Spatial inequity differences in energy poverty were shown to be significant by the study's findings. Health and education attainment might be adversely affected by energy poverty, according to the study findings. The development policy agenda is an area that most notably derives assistance from the study findings both in Pakistan and other developing countries.
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Background

Introduction

Energy is an important support base for the economic development of many nations. It is an important resource that is crucial for all households in one form or another, for cooking, heating, lighting, vital medical care, for the running of basic gadgets for communication and education and

for the achievement of anything else productive or economical, through agriculture, industry, manufacture and trade (Modi et al., 2006). Access to modern and cleaner energy is considered a welfare indicator for any society. Hence, the pattern of using energy services is closely linked with the welfare of societies. Energy poverty is central to most of the measures being taken to deal with many other challenges around the Globe. A central element of the vision and definition of energy poverty lies in ascertaining as to how much adequate amount of energy can be supplied so as to fulfill the basic demands that nations have (Gonzalez-Eguino, 2015). It has to be noted here that only a particular amount of energy can be sustained by a land.

Several studies have been conducted in the context of Pakistan as a developing economy to address the multidimensional energy poverty (Awan et al., 2013; Mahmood & Shah, 2017; Qurat-ul-Ann & Mirza, 2021). Household energy sources and fuels are also consumed more due to population growth. Energy is primarily consumed during cooking chaos. Pakistani rural areas have many poor options for obtaining energy. Due to electricity and natural gas shortages, most rural households in remote areas cook their food using biomass fuel (Fatmi et al., 2020). Using biomass fuels for cooking is a major contributor to indoor air pollution in Pakistan (Colbeck et al., 2008). According to the Multidimensional Poverty Index, approximately 69.67 percent of rural households in Pakistan lack access to clean cooking energy (Haleem et al., 2020).

There is, however, a more significant concern in developing nations (IEA, UNDP, & UNIDO, 2010). Because energy poverty is severe and intense at the household level within developing countries, it negatively impacts the environment, health, and economy (Herington & Malakar, 2016). By 2030, there are expected to be 2.7 billion additional people living in rural areas who use biomass. Many households cannot afford essential energy services as the demand for energy increases with rapid population growth (IEA, 2019). As a result of this dependence on biomass sources, women and children are unable to obtain proper education, and it is hard for them to engage in economic activity, along with many other problems like environmental degradation, deforestation, and land degradation (Faye, 2002; Jones, 2010).

Over the years, energy poverty has seen an increase and interest in research, policymaking (Liddell et al., 2012) (Okushima, 2017; Sadath & Acharya, 2017; Thomson & Snell, 2013) (Harrison & Popke, 2011), and practice. Therefore, between and within geographic zones, there are unembellished or relative differences in access to energy services (Healy, 2003; Thomson & Snell, 2013), which need to be looked into, as the impacts of energy poverty on the health of the economy are negative (Liddell & Morris, 2010).

Every economy's lifeline is its basic energy production (Sahir & Qureshi, 2007). So far, Pakistan's alarming energy poverty situation calls for special attention. Clean and affordable energy is one of UN-SDG 7's Sustainable Development Goals. Several other Sustainable Development Goals are closely related to Energy Poverty. This study focuses on two main goals: clean and affordable energy (7) and reducing inequality (10). In Pakistan, 47% of the population lacks access to electricity (IEA, 2016). 17-18% of Pakistani villages still lack electricity (NEPRA, 2019). Those population proportions from backward and remote areas still use alternative energy sources,

including kerosene and traditional biomass. Conventional energy sources are unavailable, and electricity and natural gas are expensive (PBS, 2015,17).

The goal of increasing energy access in Pakistan and reducing household energy poverty must be achieved by understanding and examining the inequalities in assessing energy sources among different geographic regions. Households primarily need these energy services to increase their welfare and achieve higher living standards. Investigating geographical differences is vital to understanding the major role of energy discrepancy.

Literature Review

Many researchers have explained the concept, relativity, and multidimensionality of energy poverty (Boardman, 1991; Bouzarovski & Petrova, 2015; Grevisse & Brynart, 2011; Li et al., 2014; Thomson et al., 2018). Energy poverty has been assessed using the MEPI approach in rural areas of Ghana. According to a study, it is evident that most groups lack cooking fuel and lighting. The low availability of electric power and the high dependence on traditional fuels, such as biomass and dung cake, were major objects of energy poverty (Ahmed & Gasparatos, 2020). However, an investigation has been conducted into household energy poverty at the regional and provincial levels in China. According to the result, although energy poverty in China decreased from 2014 to 19, the disparity still exists between rural and urban areas since rural areas are more deprived than urban areas. At the provincial level, there was also a difference in the assessment of energy sources (Liang & Asuka, 2022).

According to another study in South Africa, in order to analyze regional disparities in energy poverty, multidimensional energy poverty approaches were used to consider affordability and accessibility. The extreme energy poor live in rural areas in terms of housing accessibility and affordability (Ye & Koch, 2023). Energy prices are associated with significant personal well-being, with prominent effects among individuals in the lowest income groups (Welsch & Biermann, 2017). Researchers from various countries are concerned about energy poverty, which is more prevalent in rural areas. The digital revolution is transforming society at a rapid pace. Digitalization in the form of energy sources may also affect social stability. A study provided an analysis of the effects of digitization on multidimensional energy poverty (MEP) in rural China. Despite its intervention, digitalization has not yet benefited rural China. Rural areas have the highest level of cultural backwardness when compared with urban areas for MEP (Wang et al., 2023).

In South Asia, Parajuli (2011) focused on using renewable energy technologies to alleviate energy poverty while focusing on the efficiency of housing energy-based devices and their minimum energy requirement for daily life. Herington and Malakar (2016) documented the evidence of the potential adaptation of energy after the earthquake hit Nepal in 2015. Many people in the country transferred from clean fuel to biomass for cooking.

Moreover, a study was conducted to address the problem of energy poverty in rural households. Compared to urban households, rural households have fewer settlements and fewer opportunities

for accessing new technologies. Urban and rural India has disparities. 57% of households in rural India are energy-poor, and only 22% are income-poor, whereas in urban India, energy poverty is 28% and income poverty is 20%. In another Indian study, energy consumption problems were explored for rural and urban households in energy poverty (Jain, 2010). Ahmed et al. (2020) conducted MEP studies in the Ghana household using primary data. The authors calculated the MEPI and the result reported by them indicate that MEP varies among the different income holding households in different ways. Similarly, Ashagidigbi et al. (2020), in Nigeria calculated MEPI in MEP study using secondary data that report the value of MEP as 0.38 i.e., rural MEP (0.47) was more than urban MEP (0.17).

Hardly any literature has been developed concerning multidimensional aspects of energy poverty that have been introduced by researchers all over the world. Factors that affect multidimensional energy poverty in Pakistan were neglected (Awan et al., 2013; Qurat-ul-Ann & Mirza, 2021), and studies have only focused on the prevalence and extent of multidimensional energy poverty levels. Household surveys (PSLM), (2010-11) is the dataset. The study calculated MEPI in households at the national and provincial level (2017). A methodology was followed to generate a single index of multidimensional energy poverty in Pakistan. Results confirmed the overall rate of household level deprivation is 26.4%. Deprivation of Baluchistan is 43.1%, 29% for KPK, 24.9% for Sindh province, and 21% for the Punjab province. Rural households are more energy-deprived when compared with urban households. Household Integrated Economic and Survey (HIES) (2015-16) and (2018-19) are the datasets. The study examined energy poverty at a disaggregated level in the province of Punjab in Pakistan. Rural citizens, in contrast to the residents of urban areas, were found most impacted from the wrath of multidimensional energy deprivation than urban citizens due to inaccessibility of better energy resources, limited purchasing power (Akhtar et al., 2023), and lower income.

A major contribution of the paper is that it explores the inequalities of multiple dimensions of energy poverty. The current study did not use a single index to address multidimensional energy poverty as did previous studies, but used four dimensions comprising basic appliances and fuels to address household energy access to the best of its ability. Energy inequality is a major issue but has been neglected for many years. Our study has attempted to address the spatial and regional inequalities related to access to energy sources. These inequalities have been addressed across the four dimensions of energy poverty that have been selected. It is not only measured but also compared; for example, the inequalities in all provinces (Punjab, KPK, Sindh, Baluchistan) are compared with one another.

Methodology and data

The study used cross-sectional, secondary data from the Pakistan Social and Living Standards Measurement (PSLM) survey from the year 2019-20 to investigate the spatial inequalities of energy poverty. Almost 155988 households were used as a sample size for this survey, and SPSS software was used for the analysis. This study was influenced by the measures derived from the

multidimensional energy poverty index (MEPI) for Pakistan based on the multidimensional poverty approach of OPHI and UNDP (Alkire & Foster, 2007). The present study analyzes and addresses energy poverty status in a totally new way that has not been addressed or measured before. The use of the Uni-dimensional concept, which was utilized in previous literature to describe multidimensional energy poverty, was complex and incomplete (Mahmood & Shah, 2017). Despite this, the current approach becomes more valuable by including some essential and extra new data.

Measurement of multiple dimensions of energy poverty

In order to address the issue of household energy resources, 15 multiple variables are coded. Each of the variables is coded in binary values of 0 and 1. In this case, 0 equals the availability of the particular energy source, and 1 indicates the deprivation of that particular energy source.

Table 1: Frequency distribution of multiple dimensions of energy poverty dimension

Dimensions	Items	Frequency	%
Household appliances & cooking fuel(HACF)	0	23519	15.1
	Iron(1)	25863	16.6
	Fridge (2)	24305	15.6
	Washing machine (3)	28889	18.5
	Donkey pump (4)	36424	23.4
	Cooking fuel (5)	16988	10.9
Total		155988	100.0
Home electronics(HE)	0	120335	77.1
	LCD/ led (1)	21197	13.6
	Micro oven (2)	8973	5.8
	Landline (3)	4053	2.6
	Computer (4)	1274	.8
	Laptop (5)	156	.1
Total		155988	100.0
Lighting source & fans(LSF)	0	3412	2.2
	Lighting fuel (1)	8613	5.5
	Fans (2)	143963	92.3
Total		155988	100.0
Household services(HS)	0	7522	4.8
	Mobile (1)	60631	38.9
	Stove/ range (2)	87705	56.2
	Motorcycle (3)	130	.1
Total		155988	100.0

Source: Author's own work

PCA is utilized in this study to combine responses to various items in constructs. Principle components are linear combinations of optimally observed variables according to technical

definitions. In general, PCA reduces a large multivariate set of data into a reduced number of principle components, retaining the maximum amount of key statistical information and, most importantly, dimensional patterns (Jolliffe, 1986). Each component bears loading values relevant to each of the indicators present in the dataset. Loadings can tell us about the strength and character of relation between indicator and the principle component itself, thereby rendering information related to accuracy patterns that each component is likely to represent.

After applying the PCA to the data, we found multiple four components, as shown in Table 1. The study counts the deprivation of each dimension and then examines spatial (provincial and regional) inequalities in access to these four dimensions of energy poverty.

Analysis

To determine the mean differences between Pakistani provinces, we used one-way ANOVA. This statistical study analyzes the variance (Levens' test) for a significance level of 0.05 and an F-test to confirm the significant difference between the groups. Furthermore, a post hoc analysis named Tukey HSD is applied to compare the group (province).

There is a significant disparity between the different regions of Pakistan, such as between the rural and urban regions. To observe this regional difference, a study used an independent t-test. A t-test is used to compare an independent group or sample to ensure that the variances between the groups are equal.

Results and Discussion

All dimensions are named according to the loading of the items, and their short form is used (Table 1). Now, we empirically explore the study's primary objective, which is to estimate spatial (provincial and regional) inequalities in access to four dimensions of energy poverty.

Provincial inequality of multiple dimensions of Energy Poverty

One-way ANOVA is conducted by combining a single factor (independent) variable with quantitative dependent variables (energy poverty dimensions) in order to check the significant difference in the energy poverty level of all provinces. Table 2 contains two important ANOVA tests for homogeneity of variance conducted using Levene's method. A static analysis of Levene's has been conducted to determine whether the variances of the group are equal or not. If no difference is found in variance between the comparison groups, we can say there is no such clue of inequality between those groups. Thus, a static analysis of Levene's has been conducted to determine whether this is true. The significance level should be less than .05. In our estimation, Levene's statistics show a correlation coefficient of .000, indicating a significant difference in the homogeneity of variances among the groups for the entire energy poverty dimension. Since the homogeneity of variance requirement has not yet been met, we need to ensure that this difference is statistically significant.

Table 2: ANOVA test of homogeneity of variance

Dimensions	Levene's Statistics	Sig	F-stat	Sig
HACF	1020.139	.000	3299.593	.000
HE	1961.657	.000	586.000	.000
LSF	2816.790	.000	689.221	.000
HS	505.160	.000	2140.108	.000

Source: Authors calculations

To determine whether there are significant differences between groups, the F ratio value should be significant because each province's F ratio is higher and statistically significant at a P value of .000. As results confirm, all of the energy poverty dimensions are accessed differently in different provinces. All province's mean values differ statistically significantly from each other, as the Tukey HSD results show (See Appendix 1). These estimations confirm that Pakistan is facing an inequality in energy poverty at the provincial level. Punjab is the only province that provides the entire energy source at best other provinces. Balochistan has lower access to two basic dimensions (HACF and HE) of energy poverty than other provinces. Hence, we can reject the null hypothesis (no significant provincial differences in accessing multiple dimensions of energy) and support the alternate hypothesis.

The third dimension, which contains fans and lighting fuel, does not show much provincial deference, but these small disparities are significant and support the alternate hypothesis to be true. There are only two exceptions in Pakistan that first calculate the single index of multidimensional energy poverty and then analyze the energy poverty status for provinces. The result confirmed that the energy poverty status of each province varies (Mahmood & Shah, 2017; Qurat-ul-Ann & Mirza, 2021).

The following figures also show the provincial inequality level. We can see that a major provincial difference is found in the HACF and HE dimensions; the other two dimensions hold the difference, though.

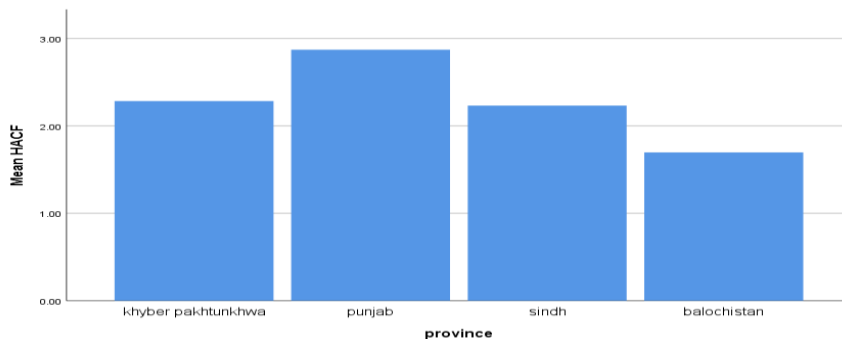


Fig 1: Mean differences of HACF by Provinces.

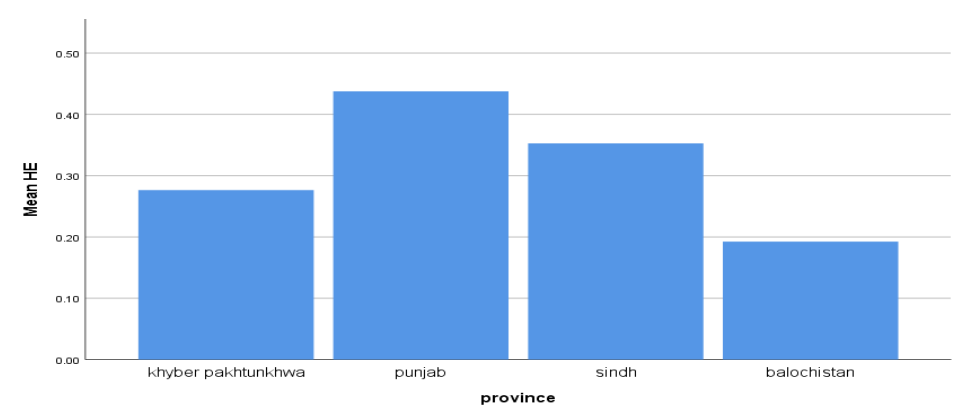


Fig 2: Mean differences of HE by Provinces

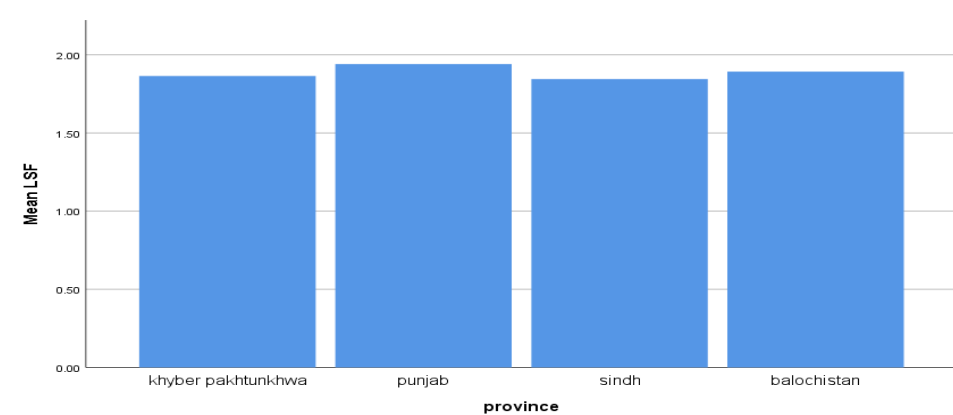


Fig 3: Mean differences of LSF by Provinces.

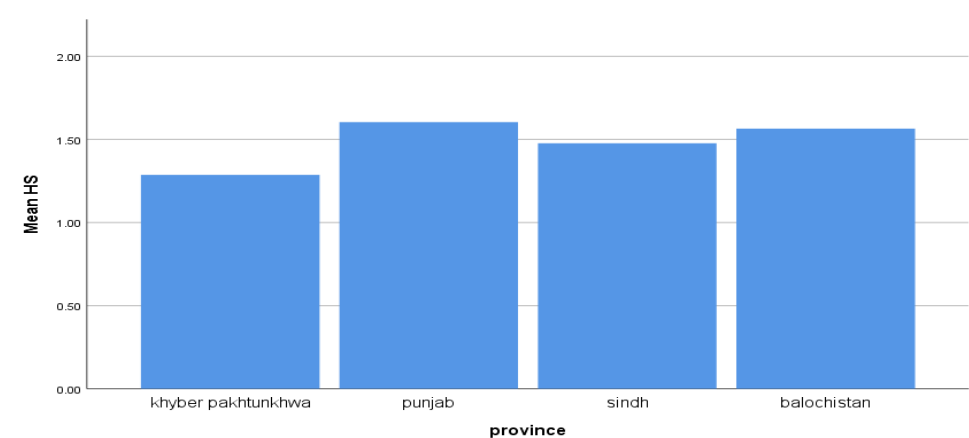


Fig 4: Mean differences of HS by Provinces

Regional inequality of multiple dimensions of energy poverty

An independent samples t-test is used to analyze regional inequality in access to multiple dimensions of energy poverty. A significant difference between rural and urban regions in access to energy poverty can be seen in the results.

Based on multiple dimensions of energy poverty, table 3 shows the mean difference between rural and urban regions. Rows represent each group. The first column contains the names of our dimensions, which are also dependent variables, and the second shows the regions. The third column shows the number of valid observations in each group, following the first column containing the dependent variable's name. According to the N column, the rural sample size is 106511, and the urban sample size is 49477 (total sample 155988). For rural groups, the mean of the dependent variable (HACF) is 2.0330, and for urban groups, it is 3.5418. It shows that rural value is lower than urban, meaning rural households have lower access than urban in this dimension. The mean difference for the other three dimensions also varies in the same way we can see from the following rows. The test will now establish if this difference is statistically significant or not.

Table 3: Group statistics

Dimensions	Region	N	Mean	Std. deviation	Std. Error means
HACF	Rural	106511	2.0330	1.53884	.00472
	Urban	49477	3.5418	1.25126	.00563
HE	Rural	106511	.2226	.59356	.00182
	Urban	49477	.6765	1.02916	.00463
LSF	Rural	106511	1.8717	.41551	.00127
	Urban	49477	1.9642	.20383	.00092
HS	Rural	106511	1.4706	.60672	.00186
	Urban	49477	1.6128	.53896	.00242

Source: Authors' calculation

There are two versions of independent samples t-tests, depending on whether the variability of the multiple dimensions of energy poverty in rural and urban settings is assumed to be equal. Urban and rural regions have significantly different standard deviations for each dependent variable. Now the question is whether the difference is big enough to break the assumption of equal variance.

It is Levene's test that is used to determine whether two groups exhibit the same level of variability (see Appendix 2). There are two versions of the test represented by the two numbers of rows on the right side of the table. Our decision is based on Levene's test. We expect the variances (along with the standard deviations) to be the same for both groups in this test. As a result, Levene's test follows the F distribution value. When F static is greater, the sample is less likely to come from a population where variances are the same. The p-value of each dimension is .000 for F static. Thus, we can

conclude that there is a difference in variance between the two groups for each dimension. Now there is a need to check whether this difference is statistically significant. For this purpose, the two tails of the test are used; the alpha value is .000, indicating that there is a significant difference in variances. All the dimensions of energy poverty reveal statistically significant regional inequality.

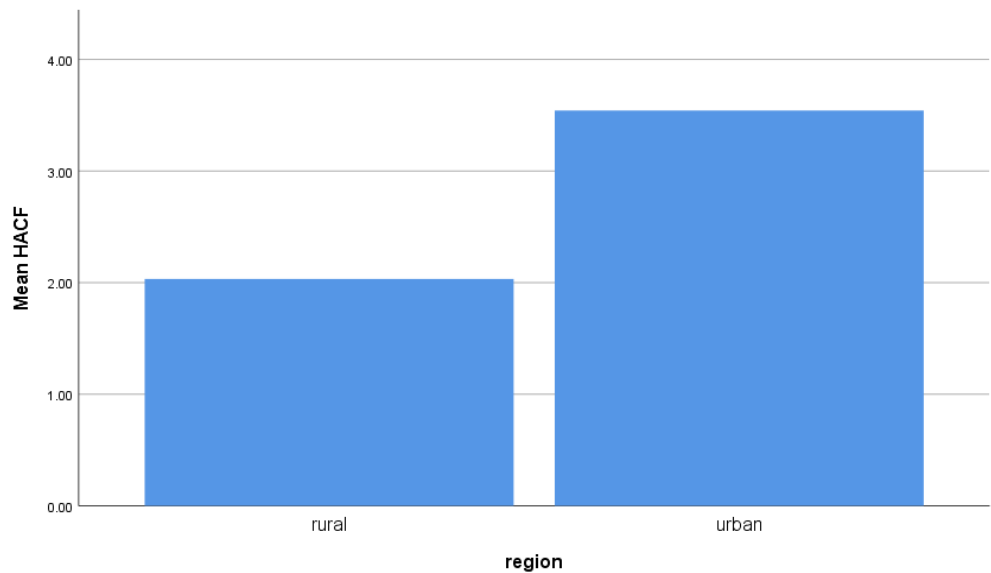


Fig 5: Mean of HAF by Region

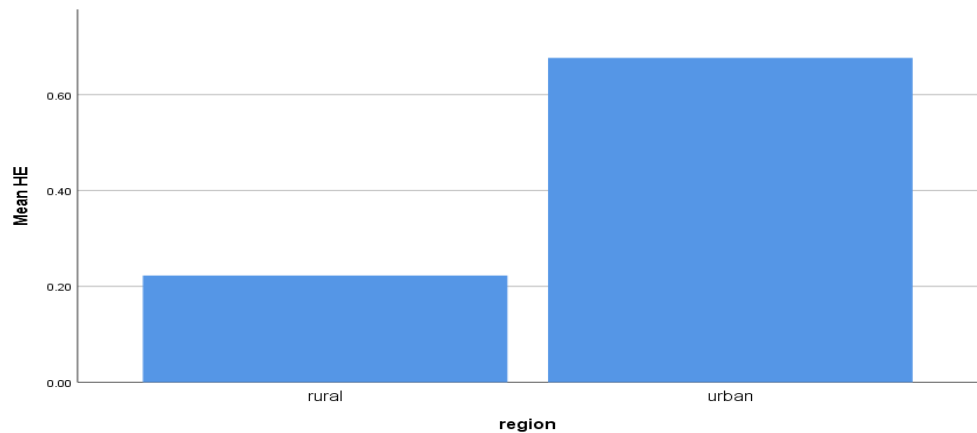


Fig 6: Mean of HE by Region

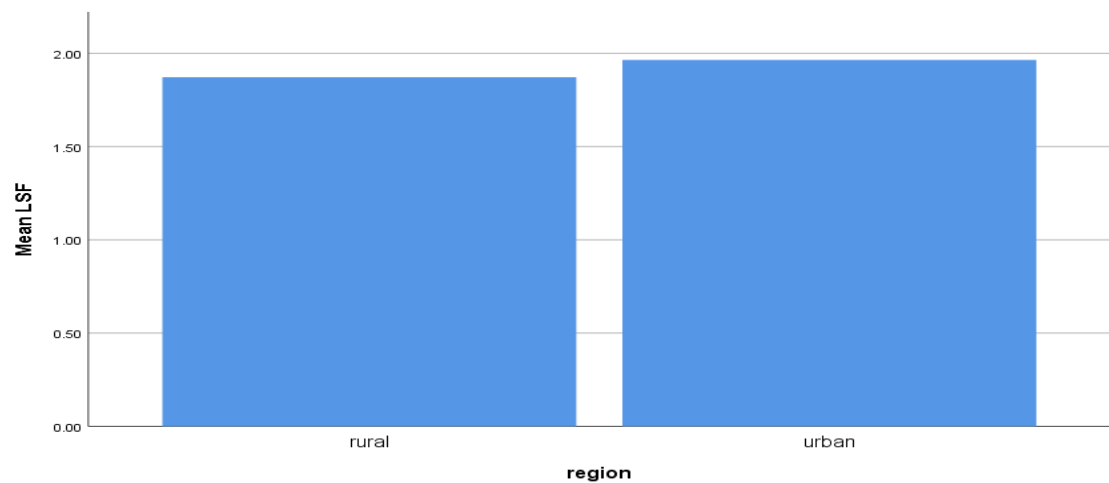


Fig 7: Mean of LSF by Region

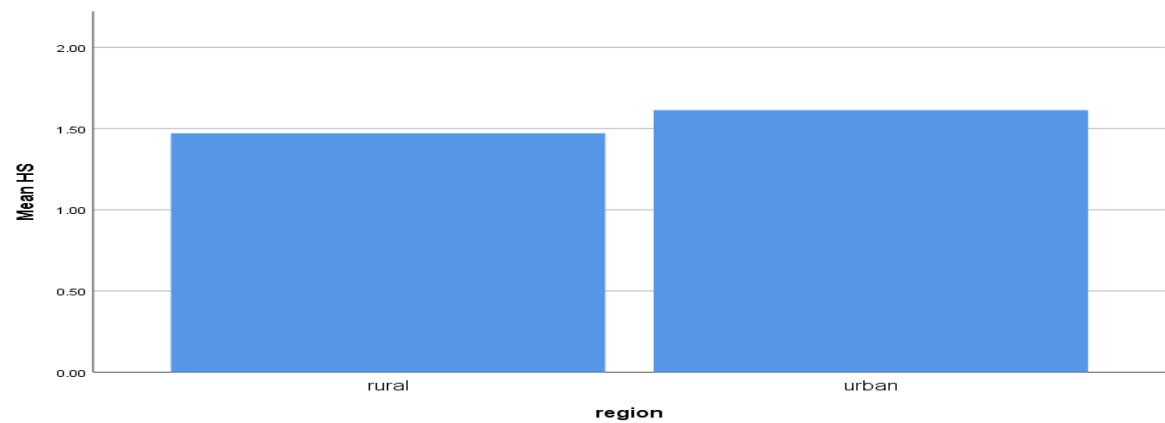


Fig 8: Mean of HS By Region

Conclusions

This research work intended to reveal the energy poverty picture in a clearer approach that has not been measured before. The purpose of this study is to provide a better understanding of the challenges and opportunities associated with energy poverty. The work was carried out with an empirical calculation of the multiple dimensions of energy poverty in Pakistan. And also ensures equitable access to clean, modern, and sustainable energy sources in Pakistan by focusing on spatial inequality of energy poverty. In order to improve access to clean energy services in the future, this study will implement policy decisions and measures. Our estimates suggest that Pakistan is facing spatial inequality of energy poverty in worse. The remote areas and especially rural areas are

facing this disparity in assessing clean cooking fuel which creates obstacles in their social as well as economic lives.

To alleviate spatial inequality and to promote inclusive energy services in Pakistan, the following policy recommendations are provided based on the results. The government should promote the use of renewable and cleaner energy sources at the national level. The national energy policy put more focus on ensuring universal access to electricity in the country with the aim of promoting households' adoption of domestic technological equipment over time and switching to clean energy for cooking. Also need to design more focused and target-based measures to provide improved, affordable, and reliable access to energy in high latitudes, and rural areas. In addition to contributing to the flourishing of economic activity and improving living standards in the area, this project has addressed some of the most pressing issues related to access to cleaner and modern fuels. In other words, there is no provision for addressing cooking needs or encouraging households to use clean energy sources in the country's existing energy policy. Accordingly, our results call for steps to improve the availability of energy sources in Pakistan, particularly the provision of modern cooking fuels. This implies that the government should ensure some projects designed to deliver electricity and related services. Moreover, rural areas and the province of Balochistan, which face higher levels of deprivation, need special attention in this context. This study can also be used as a benchmark for other developing economies that deal with multidimensional household energy poverty, especially in South Asia.

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Appendix 1

Table 1A: Post hoc Test Multiple Comparisons for HACF

(I)Province	(J)Province	Mean Difference (I-J)	Std. error	Sig.	95% confidence interval	
					Lower bound	Upper bound
KPK	Punjab	-.58728 [*]	.01097	.000	-.6155	-.5591
	Sindh	.05221 [*]	.01260	.000	.0198	.0846
	Baluchistan	.58791 [*]	.01591	.000	.5470	.6288
Punjab	KPK	.58728 [*]	.01097	.000	.5591	.6155
	Sindh	.63949 [*]	.01005	.000	.6137	.6653
	Baluchistan	1.17519 [*]	.01397	.000	1.1393	1.2111
Sindh	KPK	-.05221 [*]	.01260	.000	-.0846	-.0198
	Punjab	-.63949 [*]	.01005	.000	-.6653	-.6137
	Baluchistan	.53570 [*]	.01529	.000	.4964	.5750
Baluchistan	KPK	-.58791 [*]	.01591	.000	-.6288	-.5470
	Punjab	-1.17519 [*]	.01397	.000	-1.2111	-1.1393
	Sindh	-.53570 [*]	.01529	.000	-.5750	-.4964

Table 1B: Post hoc Test Multiple Comparisons for HE

(I)Province	(J)Province	Mean Difference (I-J)	Std. error	Sig.	95% confidence interval	
					Lower bound	Upper bound
KPK	Punjab	-.16120 [*]	.00549	.000	-.1753	-.1471
	Sindh	-.07631 [*]	.00631	.000	-.0925	-.0601
	Baluchistan	.08402 [*]	.00796	.000	.0636	.1045
Punjab	KPK	.16120 [*]	.00549	.000	.1471	.1753
	Sindh	.08489 [*]	.00503	.000	.0720	.0978
	Baluchistan	.24522 [*]	.00699	.000	.2273	.2632
Sindh	KPK	.07631 [*]	.00631	.000	.0601	.0925
	Punjab	-.08489 [*]	.00503	.000	-.0978	-.0720
	Baluchistan	.16033 [*]	.00765	.000	.1407	.1800

Baluchistan	KPK	-.08402 [*]	.00796	.000	-.1045	-.0636
	Punjab	-.24522 [*]	.00699	.000	-.2632	-.2273
	Sindh	-.16033 [*]	.00765	.000	-.1800	-.1407

Table 1C: Post hoc Test Multiple Comparisons for LSF

(I)Province	(J)Province	Mean Difference (I-J)	Std. error	Sig.	95% confidence interval	
					Lower bound	Upper bound
KPK	Punjab	-.07624 [*]	.00254	.000	-.0828	-.0697
	Sindh	.01941 [*]	.00292	.000	.0119	.0269
	Baluchistan	-.02845 [*]	.00368	.000	-.0379	-.0190
Punjab	KPK	.07624 [*]	.00254	.000	.0697	.0828
	Sindh	.09566 [*]	.00233	.000	.0897	.1016
	Baluchistan	.04780 [*]	.00323	.000	.0395	.0561
Sindh	KPK	-.01941 [*]	.00292	.000	-.0269	-.0119
	Punjab	-.09566 [*]	.00233	.000	-.1016	-.0897
	Baluchistan	-.04786 [*]	.00354	.000	-.0569	-.0388
Baluchistan	KPK	.02845 [*]	.00368	.000	.0190	.0379
	Punjab	-.04780 [*]	.00323	.000	-.0561	-.0395
	Sindh	.04786 [*]	.00354	.000	.0388	.0569

Table 1D: Post hoc Test Multiple Comparisons for HN

(I)Province	(J)Province	Mean Difference (I-J)	Std. error	Sig.	95% confidence interval	
					Lower bound	Upper bound
KPK	Punjab	-.31735 [*]	.00405	.000	-.3278	-.3069
	Sindh	-.18975 [*]	.00465	.000	-.2017	-.1778
	Baluchistan	-.27796 [*]	.00587	.000	-.2930	-.2629
Punjab	KPK	.31735 [*]	.00405	.000	.3069	.3278
	Sindh	.12760 [*]	.00371	.000	.1181	.1371
	Baluchistan	.03939 [*]	.00516	.000	.0261	.0526
Sindh	KPK	.18975 [*]	.00465	.000	.1778	.2017
	Punjab	-.12760 [*]	.00371	.000	-.1371	-.1181
	Baluchistan	-.08821 [*]	.00564	.000	-.1027	-.0737
Baluchistan	KPK	.27796 [*]	.00587	.000	.2629	.2930
	Punjab	-.03939 [*]	.00516	.000	-.0526	-.0261
	Sindh	.08821 [*]	.00564	.000	.0737	.1027

Appendix 2

Table 2A: Independent samples t-test for HACF

	Leven's test of equality		t-test for equality of means				
	F	Sig	T	Df	Sig (2-tail)	Mean differ	Std. error
EV assumed	4760.39	.000	-190.76	155986	.000	-.1508	.00791
EV not assumed			-205.56	116668.7	.000	-.1508	.00734

Table 2B: Independent samples t-test for HE

	Leven's test of equality		t-test for equality of means				
	F	Sig	T	Df	Sig(2-tail)	Mean differ	Std. error
EV assumed	26543.4	.000	-109.8	155986	.000	-.45398	.00413
EV not assumed			-91.31	65223.7	.000	-.45398	.00497

Table 2C: Independent samples t-test for LSF

	Leven's test of equality		t-test for equality of means				
	F	Sig	T	Df	Sig(2-tail)	Mean differ	Std. error
EV assumed	9563.275	.000	-46.969	155986	.000	-.09251	.00197

EV not assumed	-58.975	155569.4	.000	-.09251	.00157
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Table 2D: Independent samples t-test for HS

	Leven's equality	test	of			t-test for equality of means	
	F	Sig	T	Df	Sig (2-tail)	Mean differ	Std. error
EV assumed	2875.942	.000	-44.602	155986	.000	-.14222	.00319
EV not assumed			-46.568	107558.2	.000	-.14222	.00305