

Understanding Poverty Dynamics and Household Vulnerability in Urban Slums of Purulia (India) across the Pre and Post COVID-19 Periods

Samyakami Kaibarta

samyakamikaibarta@gmail.com

Sidho-Kanho-Birsha University

Dr. Somnath Mandal

Lovely Professional University

Dr. Arijit Das

University of Gour Banga

Dr. Manob Das

Ramananda College

Dr. Suman Paul

Sidho-Kanho-Birsha University

Research Article

Keywords: COVID-19, Poverty, Slums, Poverty dynamics, Headcount ratio

Posted Date: October 28th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11009266/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

***Understanding Poverty Dynamics and Household Vulnerability in
Urban Slums of Purulia (India) across the Pre and Post COVID-19
Periods***

Samyakami Kaibarta^{1*}, Somnath Mandal², Arijit Das³, Manob Das⁴, Suman Paul⁵

¹Samyakami Kaibarta
Research Scholar (UGC-JRF)
Sidho-Kanho-Birsha University, Purulia, W.B. India
E-mail:samyakamikaibarta@gmail.com

²Dr. Somnath Mandal
Department of Geography, Lovely Professional University, Phagwara, Punjab, 144411, India
E-mail:mandal.somu1@gmail.com

³Dr. Arijit Das
Department of Geography, University of Gour Banga, Malda, West Bengal, 732101, India
E-mail: arijit3333@gmail.com

⁴Dr. Manob Das
Department of Geography, Ramananda College, Bishnupur, Bankura, West Bengal, 722122, India
E-mail:dasmanob631@gmail.com

⁵Dr. Suman Paul
Department of Geography, Sidho-Kanho-Birsha University, Purulia, W.B. India.
E-mail: suman.krish.2007@gmail.com

Corresponding author:

*Samyakami Kaibarta
Research Scholar (UGC-JRF)
Department of Geography
Sidho-Kanho-Birsha University, Purulia, W.B. India
E-mail:samyakamikaibarta@gmail.com

Understanding Poverty Dynamics and Household Vulnerability in Urban Slums of Purulia (India) across the Pre and Post COVID-19 Periods

Abstract

COVID-19 has intensified urban poverty, disproportionately impacting informal workers, migrants, and slum dwellers due to job losses, reduced incomes, and limited access to social safety nets. The pandemic underscored structural inequalities such as inadequate housing, healthcare, and education. Assessing its impact is crucial to identifying vulnerable populations, designing targeted relief measures, and promoting sustainable urban development. This study evaluates the impact of COVID-19 on poverty dynamics across slums in Purulia, India, comparing pre- and post-pandemic periods through a questionnaire survey. ANOVA and a multinomial logit (MNL) model are used to examine variations in poverty among different worker groups and identify key influencing factors. Findings revealed significant disparities in poverty metrics such as the headcount ratio (HCR) and poverty gap ratio (PGR). Slums like Sufalpally and Bhagabandhpara exhibited the highest PGR (0.010 and 0.008, respectively). Peri-urban and mixed-development slums had higher HCR and PGR, while urban core slums like Bhagabandhpara showed pronounced income inequality. During the pandemic, over 50% of households in Sufalpally were classified as poor, followed by Sekrapara, Simuldanga, and Kasaimahalla. The study also highlighted substantial occupational shifts, with chronically poor households predominantly engaged in manual labour. Key factors influencing poverty dynamics included household monthly income, education level, and employment status. Addressing slum poverty is vital to mitigate vulnerabilities, improve access to essential services, and reduce urban inequalities, contributing to equitable pandemic recovery and resilient urban systems.

Keywords: COVID-19; Poverty; Slums; Poverty dynamics; Headcount ratio.

1 Introduction

Since February 2020, global COVID-19 cases have surged exponentially[1]. Despite some countries managing to control the pandemic, daily reported cases worldwide grew from around 500 in late February to nearly 600,000 by November, with further increases anticipated during the northern hemisphere's winter. The pandemic's epicentre shifted from China to Europe, the United States, and Latin America, with resurgence in autumn. It has spread rapidly in low- and middle-income countries in Africa and Asia, many of which face significant challenges due to weak health systems and limited social safety nets[2,3]. More than half the global population experienced some form of social distancing to control the health crisis[4]. Business activity has plummeted, driven by both policy measures and personal risk avoidance, with personal actions having a greater economic impact[5]. The International Labour Organization reported 17% drop-in global working hours during the first three quarters of 2020, equivalent to nearly 500 million full-time jobs lost. While high-income countries have implemented extensive fiscal and monetary stimulus, low- and middle-income nations have offered limited relief. Thus, COVID-19 threatened all the aspects of the environment[6,7].

The COVID-19 pandemic has significantly exacerbated global poverty, pushing millions into extreme hardship, particularly in low- and middle-income countries [8,9]. Economic disruptions caused by lockdowns, business closures, and reduced mobility have disproportionately affected vulnerable populations, especially those dependent on informal employment, which constitutes a major source of income in developing nations[10,11]. The World Bank estimated that the pandemic pushed an additional 97 million people into extreme poverty in 2020, living on less than \$1.90 per day. Income losses have further deepened inequality, with women, children, and marginalized groups being the worst affected[12–14]. School closures have not only disrupted education but also deprived children of essential nutritional support provided through school meal programs, compounding poverty-related issues. In urban areas, informal settlements have faced heightened risks due to overcrowding and limited access to health services and sanitation, while rural areas suffered from disrupted agricultural activities and market access, reducing food security [15–17]. Additionally, global economic recessions have reduced remittances, a lifeline for many poor households in developing countries. The International Labour

Organization reported a sharp decline in working hours globally, equivalent to 255 million full-time jobs lost in 2020, further aggravating poverty levels. Despite unprecedented fiscal stimulus and relief measures in high-income countries, the pandemic highlighted the inadequacy of social safety nets in poorer regions. Limited government resources in low-income nations hindered effective poverty alleviation responses[18,19]. As the pandemic persisted, recovery efforts in these countries faced challenges like debt burdens and slow vaccination rollouts[20]. Therefore, addressing COVID-19's impact on poverty requires targeted interventions, including strengthening social protection programs, creating sustainable livelihoods, and prioritizing equitable recovery efforts to support the most vulnerable populations.

The COVID-19 pandemic has significantly intensified poverty in developing countries, where fragile economies, informal labour markets, and inadequate social safety nets have magnified the crisis [21,22]. Lockdowns and restrictions disrupted livelihoods, especially for informal workers who lack job security or access to social protections [23,24]. The International Labour Organization reported that informal workers, making up nearly 90% of the labour force in some developing nations, experienced massive income losses, plunging millions into poverty. Income reductions not only exacerbated existing inequalities but also forced many households to cut essential spending on food, education, and healthcare [25,26]. Women and children were particularly vulnerable, with women disproportionately affected by job losses in service sectors and caregiving responsibilities [27,28]. School closures disrupted education for millions of children, particularly those lacking access to digital resources, and worsened child labour in low-income communities. Agricultural disruptions and limited access to markets worsened food insecurity in rural areas [17]. The World Bank estimates that the pandemic pushed an additional 70-100 million people into extreme poverty in 2020, with South Asia and Sub-Saharan Africa experiencing the largest increases. Additionally, declining remittances, a crucial source of income for many households, compounded financial hardships in countries heavily reliant on migration-related income. Government responses in many developing countries were constrained by limited fiscal capacity, leading to insufficient or delayed relief measures. Public debt burdens, coupled with reduced revenues, further restricted the ability to provide meaningful support. The pandemic has underscored the urgent need to strengthen social safety nets,

diversify income sources, and promote inclusive recovery strategies. Investments in healthcare, education, and digital access are critical for reducing long-term poverty risks. Equitable vaccine distribution and international cooperation are also essential to support vulnerable populations and enable sustainable recovery in developing countries.

Assessing the impact of COVID-19 on poverty in cities is critical for understanding and addressing the socio-economic challenges exacerbated by the pandemic[29,30]. Cities, being hubs of economic activity, have been disproportionately affected due to their reliance on sectors like retail, tourism, and informal labour markets, which faced significant disruptions [8,31]. Identifying the extent and nature of poverty caused by the pandemic is essential for designing targeted interventions to aid vulnerable urban populations [32,33]. Urban poverty assessment highlights the groups most affected, such as informal workers, women, migrants, and slum dwellers, who lack access to stable incomes, housing, and healthcare [34,35]. This information is crucial for developing responsive social safety nets and employment programs that mitigate immediate hardships. For instance, understanding income losses or food insecurity patterns allows policymakers to allocate resources efficiently, such as expanding food distribution systems or cash transfer programs in affected areas. Additionally, assessing COVID-19's impact on urban poverty sheds light on structural inequalities in cities, including gaps in housing, sanitation, healthcare, and education [36]. It provides evidence for long-term planning to build resilient urban systems that can withstand future crises. Furthermore, such assessments contribute to global development goals, including poverty eradication and reducing inequalities, by aligning urban recovery strategies with sustainable development frameworks. They also enable cities to advocate for financial and technical support from national governments and international organizations to recover from pandemic-induced setbacks. Ultimately, understanding COVID-19's impact on urban poverty is indispensable for equitable recovery and fostering inclusive urban development.

The primary objective of this study is to examine the impact of the COVID-19 pandemic on poverty in the slums of Purulia by comparing poverty conditions, occupational patterns, and their determinants across the pre- and post-pandemic periods. To achieve this overarching objective, the study pursues five specific objectives. Objective 1 is to examine the prevailing scenario and characteristics of

poverty in the slums of Purulia. Research Question 1: What are the prevailing levels, dimensions, and key characteristics of poverty among slum households? Objective 2 is to assess the dynamics of poverty between the pre- and post-COVID-19 periods. Research Question 2: How have the level, intensity, and distribution of poverty changed between these periods? Objective 3 is to examine occupational shifts among slum households. Research Question 3: What major changes in household occupations occurred between the pre- and post-pandemic periods? Objective 4 is to identify occupational shifts across different worker groups. Research Question 4: How did occupational patterns vary among different categories of workers, particularly manual and informal workers, across the two periods? Finally, Objective 5 is to identify the factors influencing poverty. Research Question 5: What socioeconomic, demographic, and occupational factors significantly influence poverty levels, and how do their effects vary across households?

2 Materials and methods

2.1 About study area

This study was conducted in Purulia Municipality, West Bengal, India. Purulia Municipality is the largest municipality in the district and the only class I town with a total size of 14.08 km². Geographically, this municipality is located at 23°19'33" N to 23°41'30" N and from 86°22'10" E. This municipality comprises 114 slums (registered and unregistered) in 23 wards. Ward no 18 has the largest concentration of slum dwellers, while Ward no 3, 13, and 23 have experienced the emergence of both registered and some unregistered slums. Purulia Municipality serves as the commercial gateway between West Bengal and Jharkhand and it is the headquarters of the district. Meanwhile, this urban centre has experienced an increasing trend of urbanization during the last decade. Previously, the development was observed in the core of the city (Chowk Bazar) but over time it shifted towards the north-eastern portion of the city (Deshbandhu Road), particularly at the fringe of cities through the process of the edge expansion. A group of businessmen and entrepreneurs established a market area to provide more modern and advanced services and facilities to the elite-class residents of the town. Apart from that, Medical Colleges, Universities, Schools, and other educational sectors developed here over time. Therefore, Purulia municipality acts as a pull factor of commercial, educational, and infrastructural development hubs in the district [37,38].

Many people migrate to the city from the different villages of the district, as well as other states, in search of better jobs and economic opportunities. As a consequence of financial instability, they are forced to live in crowded and filthy neighbourhoods in the city. These areas are often situated near the railway track and highway. As per the census 2011, the statistics of birth and death rates indicate a higher level of migration compared to a natural population increase. The aforementioned factors have stimulated the slum expansion in the city.

2.2. Methods

2.2.1. Data collection and questionnaire survey

The current research utilized both secondary and primary data. A mixed approach has been used to collect data. Data were collected from two rounds of surveys. The initial survey was carried out in 2019, representing the pre-COVID-19 periods, and a post-COVID-19 period was conducted in 2024, after the pandemic. The survey was conducted during both pre- and post-COVID-19 periods to understand the poverty dynamics across urban slums. Structural questionnaires, focus group discussions, and oral interviews were the major parts of the survey methods. Data collection included household heads' consumption income and expenditure (such as monthly income of the households), as well as their demographic (such as age, and gender) and socioeconomic (such as educational level) attributes in the selected slums. Among 5,360 total households residing in the eight slums (*As per Census of India, 2011*), 375 households (Using Yamane method) were selected during the pre-COVID periods from the selected slums, and the same number of slum households were chosen in the post-COVID-19 periods in this study.

Most of the slums started to develop near the road, railway lines, and water bodies. Therefore, the survey was started first from the slums located along the roads. The survey was conducted at the households across the slums. If that household was unavailable then the next households were selected. The structured questionnaires were divided into two sections. Firstly, the initial section mainly dealt with respondent's social-demographic attributes, while the second section of the questionnaire mainly focused on the economic attributes of the households. Initially, the questionnaire was developed in English, then it was translated into the local dialect i.e., Bengali for better communication with respondents. Thus, the interviews

were conducted in the household head's native language (Bengali). Focus group discussion (FDGs) was conducted in each slum to understand the impact of COVID-19 on poverty during pre- and post-COVID-19 periods. 5-10 local people were chosen for FGD based on the occupational structure and socio-demographic attributes of the households. The local councillor, one coordinator and one intermediate were present during the discussion, which was recorded using an audio recorder with the participants' consent. Each group discussion lasted approximately 4-5 hours. Apart from the primary survey, this study also used secondary data from different published reports, including Detailed Project Report (DRP) on Pri-minister Ayas Yojana (PMAY) (Housing for All) for Beneficiary Led Construction (BLC) under Housing for All in slums, Purulia Municipality, 2015–2016, Census of India (2011).

2.2.2. Sampling technique and determination of sampling size

The households residing in the slums were the primary unit of analysis in this study. The household head (HH) was considered the proper representation for the survey with diverse demographic and socio-economic conditions. According to the information provided by the Purulia municipal authorities and Census of India (2011), there were 5360 total households across 8 slums. Therefore, it is essential to determine the number of households (sample size) to make the study reliable and robust. Determining the sample size is crucial for ensuring the validity and reliability of research findings. An appropriate sample size enhances the precision of estimates, reduces sampling error, and increases the study's statistical power, minimizing the likelihood of Type I and Type II errors[39]. An overly small sample can lead to unreliable results, while an excessively large sample may waste resources [40]. Additionally, a representative sample size ensures generalizability to the target population[41]. Researchers should consider factors like study design, population size, and desired confidence levels during sample size determination. In this study, the method proposed by Yamane (1973) has been used to determine the sample size across the slums (*Equation 1*):

$$n = N / (1 + Ne^2) \dots\dots\dots[1]$$

where N is the household size (5360) and e is the level of precision (here ± 5 per cent precision level) assuming a 95 per cent confidence level and $p = 0.5$. After getting the sample size of 372 (rounded up to 372.22) using the above equation

(*Equation 1*). Since the number of Households in the slum of Purulia municipality is known and finite, this research uses Yamane's formula for sample size selection. The sample size for each slum has been calculated employing a proportional allocation method based on *Equation 2*.

$$n_1 = n * (N_1/N) \dots\dots\dots [2]$$

where, n_1 = sample size for selected, n = total sample size, N_1 = selected slum households and N = Total households of the selected slums. For example, the estimated sample size for Sekrapara slum is as follows:

$$n_1 = [372 * (1265/5360)] = 372 * 0.0236 = 88.10 \text{ or } 88 \dots\dots\dots [3]$$

A comprehensive list of surveyed households from each chosen slum is given in *Table 1*. Thus, based on the equation above, 375 households were selected across eight selected slums with an average number of households of 47.

2.2.3. Criteria for the selection of slums

Identifying slums in Indian cities involves a combination of spatial, socioeconomic, and infrastructural indicators. Slums are typically characterized by high population density, substandard housing, lack of basic services (e.g., water, sanitation, electricity), and insecure tenure. Household surveys and census data are also crucial for identifying socio-economic aspects like poverty and employment status [42]. Collaborations with local authorities and field verification further validate slum boundaries. In India, slums are categorized into three classes: these are: notified¹, recognized and non-notified² Slums. In Purulia municipality, there were 114 notified and non-notified slums. Among the 114 slums, eight most dilapidated slums were selected in this study. The slums were selected based on two criteria: (a) four slums were selected based on the concentration of slum population (slums with more than fifty per cent households), and (b) four slums based on slum area to total ward area (where slum areas constitute more than 20% of ward area) [37,43](*Fig. 1*). According to the information provided by the ward councillors, there were 15,264 people across the eight slums. There are spatial variations of poverty within the city among the households living in slum areas [44]. Therefore, it is crucial to understand the variation of poverty within the city.

¹Notified slum: Areas notified as slums by the local government and authorities.

²Non-notified slums: The areas notified by the local urban bodies, but not recognized by the state government.

Table 1:Slums selected in this study

Ward no.	Ward area (in km ²)	Total population	Slum area (in km ²)	Slum population	% of slum area	% of slum population	slums HHs	Name of the slum	Sample HHs
1	0.514	6065	0.073	3194	14.19	52.66	712	Deshbandhu Rd.	50
2	0.308	5009	0.014	1624	4.57	32.42	361		
3	1.185	5156	0.000	0.00	0.00	0.00	0.00		
4	1.051	4740	0.147	1676	14.01	35.36	372		
5	0.498	8087	0.051	572	10.30	7.07	127		
6	0.598	6256	0.066	1439	10.98	23.00	320		
7	0.683	7251	0.067	1357	9.87	18.71	302		
8	0.265	6096	0.079	1010	29.94	16.57	337	Kasaimahalla Slum	24
9	1.030	8534	0.103	1762	9.99	20.65	392		
10	0.327	7683	0.016	1635	4.77	21.28	363		
11	1.227	5545	0.084	2931	6.84	52.86	651	Telkal Para Slum	46
12	0.193	3535	0.008	1588	4.09	44.92	353		
13	0.297	1799	0.000	174	0.00	9.67	39		
14	0.150	3616	0.044	1312	28.98	36.28	292	Bhagabandh Slum	20
15	0.130	2888	0.026	1372	20.18	47.51	392		
16	1.231	6558	0.087	3710	7.10	56.57	824	Simuldanga Slum	58
17	0.154	4369	0.040	1761	25.85	40.31	391	Napit Para Slum	27
18	0.376	7215	0.074	4426	19.70	61.34	1265	Sekra Para Slum	88
19	0.112	3729	0.012	843	10.88	22.61	281		
20	0.192	4374	0.012	560	6.32	12.80	124		
21	1.182	5822	0.312	2885	26.41	49.55	888	Sufal Pally Slum	61
22	0.888	3451	0.054	968	6.10	28.05	215		
23	0.388	3658	0.041	1234	10.46	33.73	258		
Σ	12.978	121436	1.411	37865	10.87	31.18	9219		375

Note. Red color indicates slums with more than 50% population and Violet color indicated slums with more than 20% slum population

In this study, slums were categorized into three classes. These were: urban core, peri-urban and mixed development areas. One slum was selected from the urban

core due to significant traffic congestion, and high population density (Bhagabandhpara slum). Meanwhile, Kasaimahalla, Deshbandhu Road By lane, Sekrapara Slum, and Napitpara were selected from the peri-urban area, where the density of the population is lower than the urban core area. Finally, three slums (Simuldanga, Sufalpally, and Telkalpara) were selected from mixed development areas that contain both agricultural areas and residential areas with lower population density and large open spaces (*Table 2*).

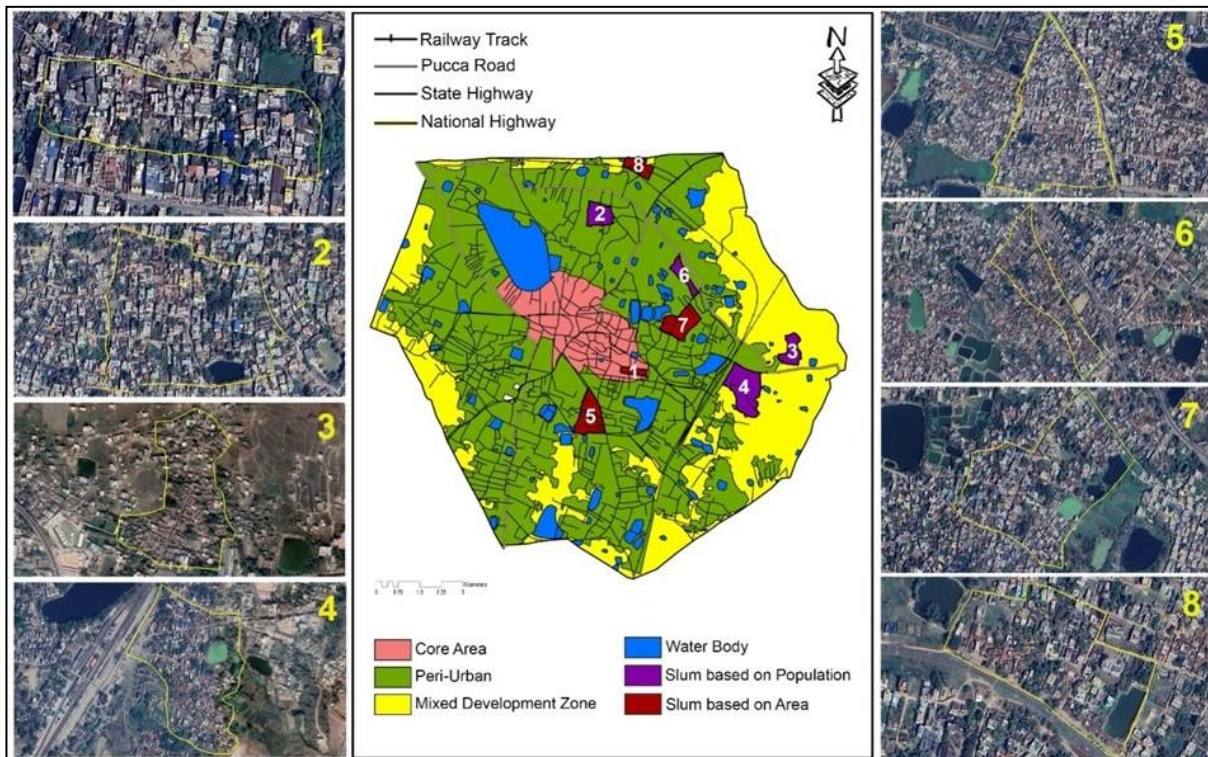
Table 2: Key characteristics of different zone

Zone	Key characteristics	Selected slum (s)
Core	Core of the city often characterised by overcrowding population, environmental stress and high cost of living. The concentration of retail, commercial and service business are very high in this zone. Significant traffic congestion is also observed in core area.	1.Bhagabandhpara
Peri-urban	A peri urban area lies outside of the city, characterised by a mixed of both rural and urban features. The peri-urban area plays an important role in an expansion of urban growth. Here, the density of the development is slower than the core area.	1.Kasaimahalla 2. Deshbandhu Road By lane 3. Sekrapara 4. Napitpara
Mixed development	A mixed development zone contains agricultural, residential, industrial and commercial areas.It exhibits an integration of various land uses.	1.Simuldanga 2. Sufalpally 3.Telkalpara

2.2.4 Categorization of the households

In this paper, we identified poor and non-poor households based on their monthly per capita consumption expenditure (MPCE), employing a given poverty threshold. Apart from poor and non-poor groups, vulnerable non-poor households were identified which is crucial from a policy perspective. These households are above the poverty line but stand at a greater risk of entering into poverty due to unfavourable shocks, such as the COVID-19 pandemic [45,46]. This research followed the

previous research conducted by Dang and Lanjouw, 2017[47] in establishing the vulnerability line using a predetermined vulnerability index. In this study, the household was considered as vulnerable non-poor when its MPCE is twice the national poverty line. In a nutshell, vulnerable non-poor are more economically stable than poor people but not as secure as non-poor or middle class. Accordingly, three groups have been identified including poor, vulnerable non-poor, and non-poor to analyse the poverty dynamics of eight surveyed slums. This research tried to understand the level of poverty and its dynamicity during pre-COVID and post-COVID periods in slums. This study utilized the Rangarajan committee's poverty line estimations for the year 2011-2012 [48], which were INR 1407 (USD 16.73) and INR 972 (USD 11.56) MPCE for urban and rural households, respectively [50]. This research utilized the headcount index (HI), the poverty gap index (PGI), and relative



poverty (RP) to assess the uni-dimension of poverty across the selected slums.

Fig. 1: Location of selected slums based on concentration of slum population and area of slum.

2.2.5. Assessment of poverty

2.2.5.1. Assessment of poverty headcount ratio

To estimate the present scenario of poverty, the headcount ratio method of measuring poverty has been used. The HI is a widely used measure that measures the proportion of the population considered poor, often denoted by P0[50]. People classified as poor are those whose household's MPCE is below the poverty threshold.

$$H = \frac{q}{n} \dots \dots \dots [4]$$

Where, q = number of individuals or households whose income is below the poverty line, n= Total population.

This measure has some considerable limitations. Firstly, it failed to identify the degree of poverty, which is crucial for policy analysis. Secondly, it fails to specify the severity of poverty among the impoverished, and the easiest method to diminish the headcount index is to distribute assistance to individuals marginally above the poverty threshold[51]. Poverty estimates have to be computed for individuals rather than households.

2.2.5.2. Assessment of poverty gap

To overcome the aforementioned drawback, this research employed PGI to assess the depth and severity of poverty, seeking to observe the gap between poor people and the poverty line among slum households. This method assessed how far a household was from reaching the poverty line [52]. The PGI is expressed as:

$$P_a = \frac{1}{n} \sum_{i=1}^m \left(\frac{z-y_i}{z} \right) \dots \dots \dots [5]$$

where, m = number of households below the poverty line, n = total sample population, Z= poverty line and y_i = income of an individual.

2.2.5.3. Assessment of relative poverty

Earlier, researchers used absolute measures focusing on basic needs, but later, shifted to relative measures that emphasized social inclusion. A combined approach is important to consider both aspects together[53]. This study uses the Gini coefficient to measure relative poverty based on household income.

$$G = 1 - \sum_{i=1}^n (X_i - X_{i-1})(Y_i + y_{i-1}) \dots \dots \dots [6]$$

Where, X_i = Cumulative population share, Y_i = Cumulative income share.

The Lorenz curve visually shows income or wealth inequality in a population. It plots the cumulative share of total income against the cumulative percentage of the population. A perfectly equal income distribution is shown as a straight 45-degree line, called the "line of equality". In contrast, a highly unequal distribution appears as a curve further away from this line. The closer the Lorenz curve is to the line of equality, the more balanced the income distribution. Greater gaps between the Lorenz curve and the line of equality indicate higher inequality. The Gini coefficient, calculated from the Lorenz curve, is a numerical measure of inequality. It ranges from 0 (perfect equality) to 1 (maximum inequality). In this study, the Lorenz curve is used to represent income distribution across slum households by plotting their cumulative income shares. The Gini coefficient quantifies this inequality, with higher values showing greater income disparity and lower values indicating more equal distribution. This analysis helps reveal the variation in income inequality across the slum.

2.2.5.4. Assessment of poverty dynamicity

A transitional matrix has been used to understand the poverty dynamics [46,54], in which poor, vulnerable non-poor and non-poor households were distinguished based on their MPCE and analysed the dynamics of poverty status during pre- and post-COVID-19 periods (*Table 3*). This study exhibits the occupational shifting across poverty dynamics groups from pre- to post-COVID-19 periods in different slums using a radar diagram. Major occupational categories of slum dwellers have been classified as manual labour / unskilled jobs, skilled/professional jobs in the public sector, skilled/ professional jobs in the private sector, domestic / service work, self-Employed/small businesses.

Table 3:Transitional matrix for assessing dynamicity of poverty

Nature of Poverty	Poor	Vulnerable non-Poor	Non-poor	Total
Poor	p_1	p_2	p_3	$p_1+p_2+p_3$
Vulnerable non-Poor	p_4	p_5	p_6	$p_4+p_5+p_6$
Non-poor	p_7	p_8	p_9	$p_7+p_8+p_9$
Total	$p_1+p_4+p_7$	$p_2+p_5+p_8$	$p_3+p_6+p_9$	Z

Source: Computed by author.

Note. p_1 = Number of poor households in pre-COVID and post-COVID situations, p_2 = Number of households that were poor in pre-COVID but vulnerable non-poor in post-COVID situations, p_3 = Number of households that were poor in pre-COVID but non-poor in post-COVID situation, p_4 = Number of households that were vulnerable non-poor before COVID-19 but poor in the post-COVID context, p_5 =Number of vulnerable non-poor households in both situations, p_6 = The number of vulnerable non-poor households in the first round of survey but non- poor in after pandemic, p_7 = Number of non-poor households in pre-COVID but poor in post-COVID era, p_8 = Number of homes that were non-poor before COVID-19 but are vulnerable non-poor in the post-COVID context, p_9 = Number of Non-poor households in both pre-COVID and post-COVID situation, Z = Total number of household of the slum.

2.4 Data analysis

A number of statistical analyses have been employed to understand the impact of COVID-19 on poverty during pre- and post-pandemic periods. A one-way ANOVA (Welch's) test was employed to evaluate if the various occupations, including manual labour/ unskilled jobs, skilled/professional jobs in the public sector, skilled/professional jobs in the private sector, domestic / service work, and self-employed/small business were significantly different for various natures of poverty. Subsequently, Tukey's Post Hoc test was applied to understand how different occupational shifts affected various poverty groups.

A multinomial Logit (MNL) model has been used to examine the factors affecting poverty dynamics across the slums. The MNL is a robust tool for analysing factors influencing poverty at the household level, particularly when poverty is categorized into multiple levels or dimensions [55,56]. Unlike binary models, the MNL allows researchers to investigate how predictors like monthly income, educational level, employment status, and dependency ratio influence distinct poverty categories, such as extreme poverty, moderate poverty, or no poverty. Monthly income is a primary determinant, with higher income generally reducing the likelihood of households falling into severe poverty[57]. Educational level significantly impacts poverty status as well, with increased education enhancing employability and earning potential, leading to upward mobility in poverty categories[58]. Employment status acts as a key variable in this model, distinguishing between households that rely on stable incomes versus those dependent on irregular or informal employment[59]. The

dependency ratio, which measures the proportion of non-working members to earners in a household, is also pivotal. High dependency ratios often strain household resources, increasing the probability of falling into extreme poverty. The MNL model's strength lies in its ability to quantify the relative impact of each factor on different poverty outcomes. For instance, it can estimate the likelihood of a household transitioning from extreme to moderate poverty given an increase in monthly income or a shift in employment type. All the statistical analysis was carried out using STATA (version 14) software. The details of the research framework are presented in *Fig.2*.

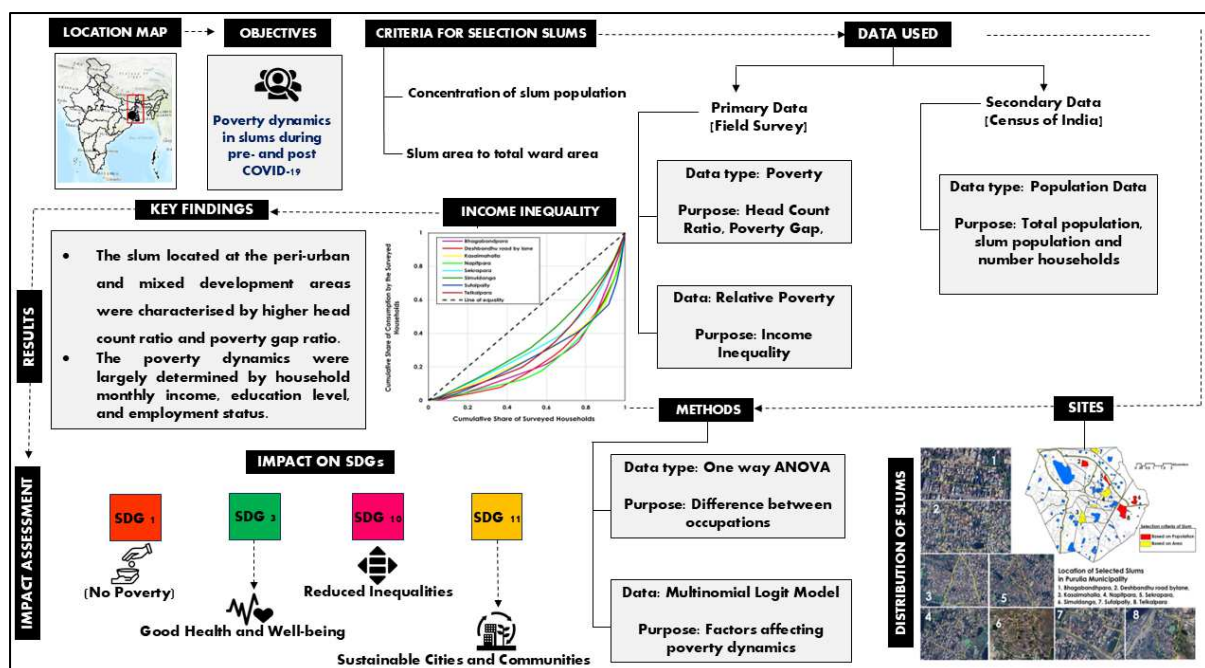


Fig.2: Research framework used in this study.

3 Result

3.1 Scenario of poverty across the slums

3.1.1 Absolute poverty

The HCR showed a diverse poverty pattern, with Simuldanga having the highest HCR at 83.56%, indicating over one-third of its households living in poverty. On the other hand, Sufalpally (74.56%), Kasaimahalla (72.50%), and Deshbandhu road by lane (71.56%) also had HCR above 70%, highlighting severe poverty levels. Sekrapara, on the other hand, had a lower HCR of 55.87% but still had more than

half of its residents impoverished. Bhagabandhpara, Napitpara, and Telkalpara had HCRs above 60%, indicating widespread and pervasive poverty (Fig.3).

There were also variations of the PGR among the households living in the slum areas. The results showed that Sufalpally and Bhagabandhpara had the highest PGR with values of 0.010 and 0.008 indicating a significant income gap, indicating that individuals in these areas are further from escaping poverty due to their financial needs. Telkalpara had the lowest PGR at 0.001, suggesting a shallow poverty depth among its residents. The moderate PGR was found in Kasaimahalla, Deshbandhu Road by Lane, and Sekrapara. The results also showed that there were spatial variations of poverty across the core, peri-urban and mixed development areas. The most of households living in peri-urban or mixed development areas (Simuldanga, Sufalpally, Kasaimahalla, Deshbandhu road by lane) were characterized by higher deprivation and high HCR and PGR (Sufalpally). On the other hand, the slums located in the core areas were characterized by a relatively low heat count ratio and a high poverty gap.

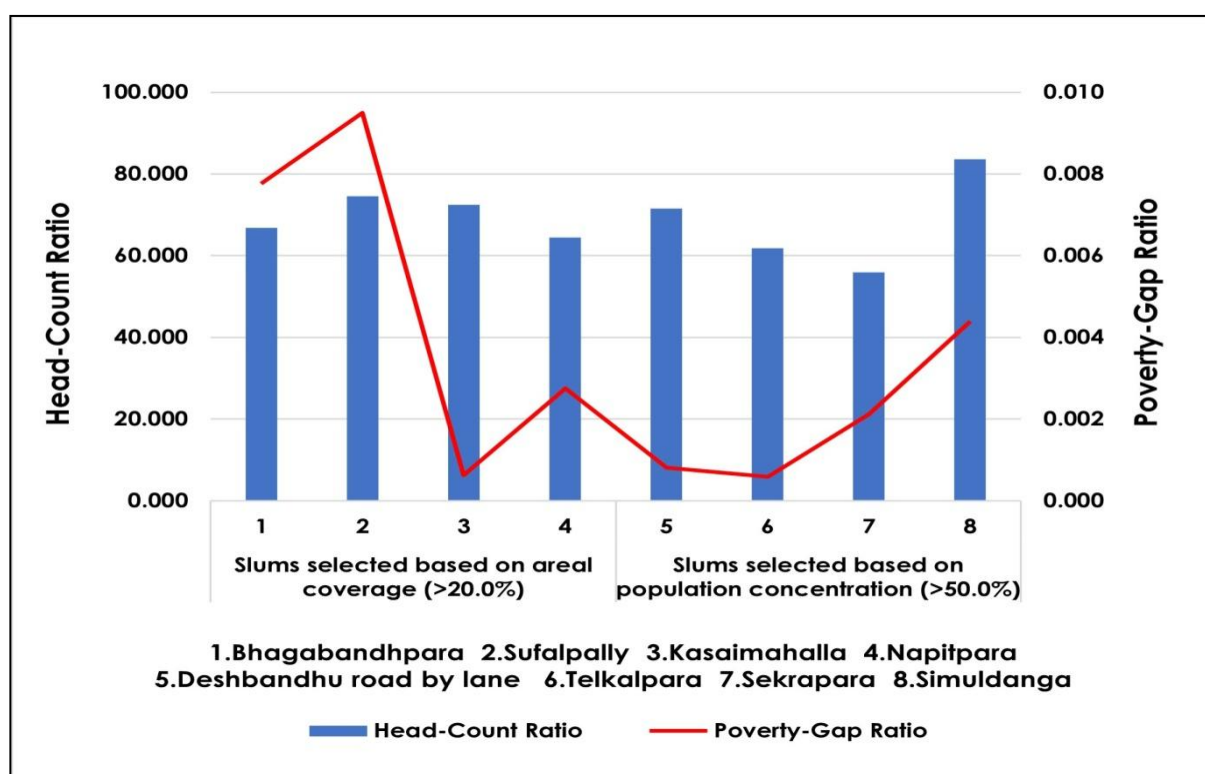
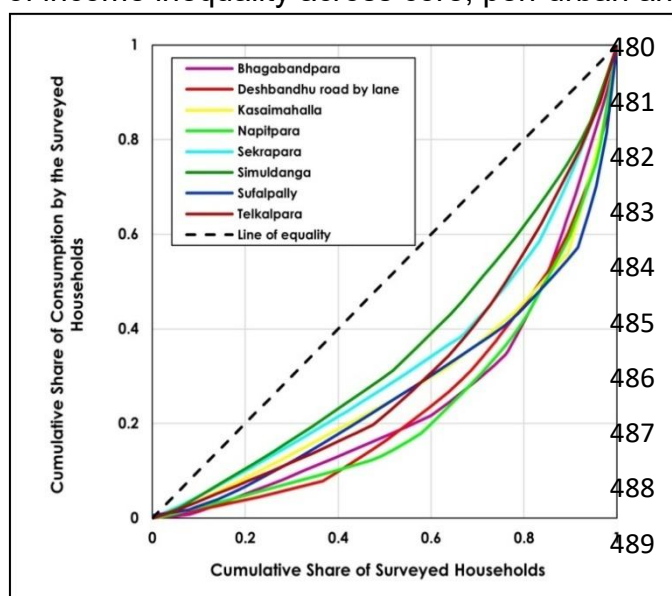


Fig. 3: Head count ratio (HCR) and Poverty gap ratio (PGR) among the slum dwellers

3.1.2 Relative poverty

The Lorenz curve revealed a significant income disparity among the slum areas. Napitpara had the highest Gini coefficient value of 0.531, indicating a significant degree of income inequality among the households (*Fig.4*). Deshbandhu Road by Lane and Bhagabandhpara also showed a high Gini coefficient value, suggesting income inequality was a prevalent issue. Kasaimahalla, Telkalpara, and Sufalpally show moderate income disparity, with Gini coefficient values of 0.430, 0.390, and 0.379 showing a relatively balanced income distribution. Simuldanga and Sekrapara have the lowest levels of income inequality, with Gini coefficients of 0.341 and 0.283, indicating a more equitable distribution of income among the households.

In the case of the spatial variation, it was found that there were substantial variations of income inequality across core, peri-urban and mixed development areas. The core



areas were characterized by relatively significant income inequality. In contrast, slums with mixed development zones showed a moderate-income inequality, reflecting a relatively balanced income distribution. However, slums in the peri-urban area experience the most dynamic Gini-coefficients.

Fig. 4: Income inequality among the selected slums HHs

3.2 Poverty dynamics across various slums

Sankey diagram(*Figure 5*)shows the poverty dynamics across the slums during pre- and post-COVID-19 periods in Purulia Municipality. There were significant transformations of poverty during pre- and post-COVID-19 periods across the slum areas. For example, Sufalpally was significantly affected by chronic poverty. Over 50% of the households remained consistently poor during pre- and post-COVID-19 periods in Sufalpally, followed by Sekrapara, Simuldanga, and Kasaimahalla. Despite the persistence of poverty, 24% of households in Sufalpally managed to

transition out of poverty. Particularly, 16.67% shifted into the vulnerable non-poor category, and 7.14% attained the non-poor status.

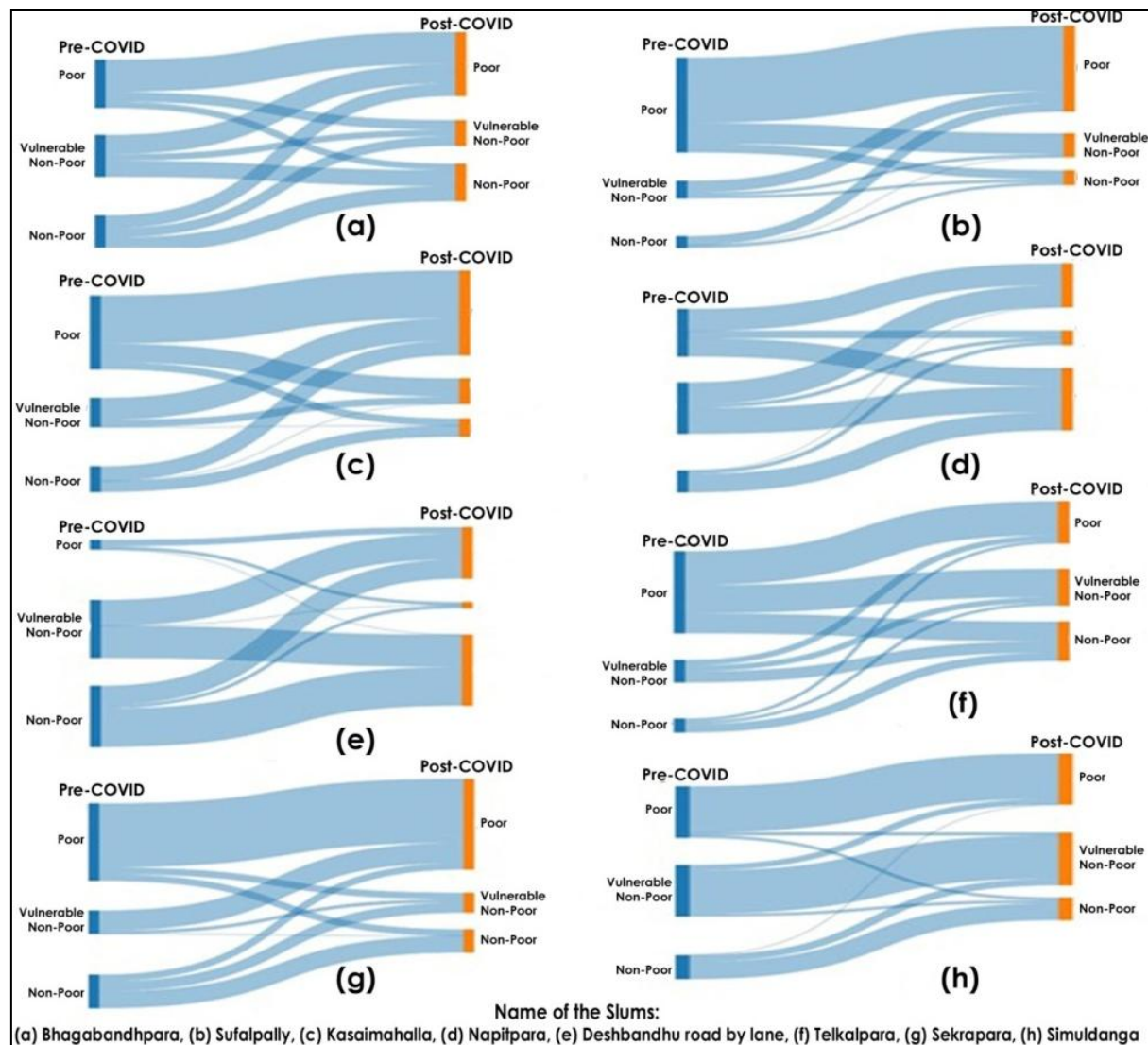


Fig.5: Poverty dynamics across various slums in Purulia during Pre-Covid to Post-Covid span.

On the other hand, Napitpara and Deshbandhu Road by Lane show the lowest rates of chronic poverty, with only 18.18% and 20% of households remaining poor, respectively. The results also showed that Bhagabandhpara had an increase of 12.5% in the poor category, coupled with declines in both the vulnerable non-poor and non-poor households by 4.76% and 2.38%, respectively. In Simuldanga, a significant 36% of the population falls under the vulnerable non-poor category. This group, while not classified as poor, remains at considerable risk of slipping into poverty, especially under economic shocks similar to those caused by COVID-19.

Napitpara and Deshbandhu Road by Lane, on the other hand, show slight improvements in poverty reduction among the poor and vulnerable non-poor groups, with downward shifts of 3.02 and 5 percentage points for the poor and 6.06 and 2.5 percentage points for the vulnerable non-poor, respectively. From the findings of the results, it was observed that there was significant mobility among the households across the slums. For example, a relatively higher rate of upward mobility was reported from Deshbandhu Road by Lane (25 %), Telkalpara (16.67%), and Napitpara (15.16%) shifting where from the poor to the non-poor category, respectively (*Supplementary Table S1*).

3.3. Occupational shift during pre to post-COVID-19 as resilience to pandemic

Figure 6 revealed a complex and multifaceted scenario of occupational shifts across poverty dynamics among the households across the selected slums during the pre- and post-COVID period. The household groups were classified into five categories based on the poverty dynamics and its impact on the households. These were: the chronically poor group, self-employed group, poverty escape group, poverty entry group and non-poor group.

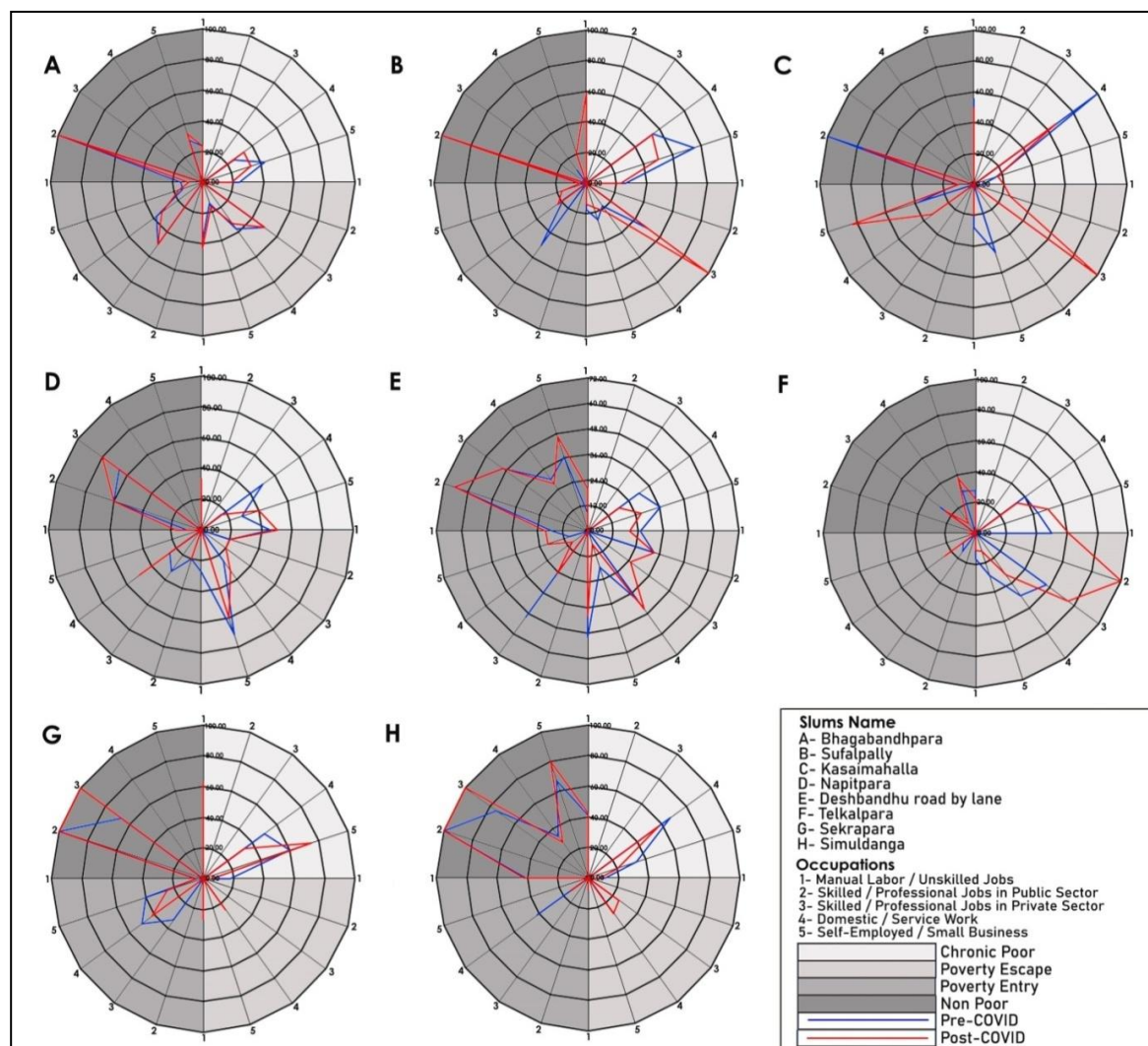


Fig.6:Occupational shift during pre- and post-COVID-19 periods

3.3.1. Chronically poor group: increased reliance on manual labour and decrease in domestic work

The chronically poor households group living in Napitpara and Deshbandhu Road by Lane exhibited the highest increase in households engaged with manual labour or unskilled jobs during post-COVID-19 periods. Conversely, Kasaimahalla and Telkalpara show a decrease in manual labour engagement by 5.56 and 5.65 percentage points, respectively. A moderate change in manual labour engagement was reported in Sufalpally (6.92 %), Sekrapara (6.64 %), and Simuldanga (1.57%). Domestic work engagement dropped significantly from pre-COVID to Post-Covid in several slums, most notably in Kasaimahalla (33.35%), Sekrapara (16.67%), and Deshbandhu Road by Lane (11.82 %), Simuldanga (9.52%), and Telkalpara (6.67%). In Bhagabandhpara, however, the percentage of domestic workers increased from 25% during pre-COVID-19 to 33.33% during post-COVID.

3.3.2. Self-employment trends: mixed impact on economic mobility

Self-employment has shown a mixed trend across the chronically poor group. Sekrapara experienced an increase of 15% among self-employed households, followed by Napitpara (11.43%) and Telkalpara (7.14 %). On the other hand, Sufalpally witnessed the highest reduction in self-employment (25 %), followed by Simuldanga (13.33 %), Bhagabandhpara (9.52 %), and Deshbandhu Road by Lane (9.70 %).

3.3.3.Poverty escape group: persistent manual labour and limited skilled employment

Among the poverty escape group, manual labour engagement remained relatively consistent between the pre-and post-COVID-19 periods in Kasaimahalla and Telkalpara, with the highest increase observed in Kasaimahalla (14.44 %). Telkalpara and Napitpara also showed an increase in manual labour engagement. Although there was a limited engagement in skilled or professional jobs among the group, there was a slight increase in private sector employment observed in slum areas like Kasaimahalla, Sufalpally, Deshbandhu Road by Lane, Simuldanga, Napitpara, and Telkalpara.

3.3.4 Poverty entry group: decrease in manual labour and rise in domestic work

The poverty entry group also demonstrated notable occupational shifts, particularly concerning manual labour. In Kasaimahalla, there was a significant decline in manual labour suggesting a reduction in dependence on unskilled jobs (27.27 %). In some selected slums (such as Telkalpara and Sekrapara), there was an increase in manual labour engagement. In the case of Sufalpally, there was an increase of domestic work (increased by 33.33%) and small businesses (increased by 44.87%), respectively.

3.3.5 Non-poor group: mixed trends in employment stability

The non-poor households showed mixed trends in manual labour engagement. Bhagabandhpara (reduced by 4.76%) and Kasaimahalla (reduced by 1.11%) experienced a slight reduction in the engagement of manual labour engagement. On the other hand, Napitpara, Deshbandhu Road by Lane, Simuldanga, Sekrapara, and Sufalpally, showed an increase in engagement in manual labour. The households with small business engagement increased in Sufalpally (20.67 %), Simuldanga (13.33 %), Deshbandhu Road by Lane (10.30%), Telkalpara (8.93%), and Bhagabandhpara (4.76 %). However, in other slums like Kasaimahalla, Napitpara, and Sekrapara, the non-poor group remains disengaged from domestic work and small businesses.

3.4. Occupational shifting among different groups

Table 4 shows the result of the ANOVA (Welch's) test, providing critical insights related to the significant differences between households. The occupations were normally distributed among manual labour/ unskilled jobs, domestic / service work, and self-employed/small business. However, labour engaged in skilled/ professional jobs in the public sector and skilled/ professional jobs in the private sector did not follow the normal distribution during the preliminary analysis.

Table 4: ANOVA table for Occupational Shifting of slum dwellers

Occupation	F	df ₁	df ₂	p
Manual Labour / Unskilled Jobs	1.35	3	14.1	0.298
Domestic / Service Work	2.4	3	13.7	0.102
Self-Employed / Small Business	3.48	3	14.6	0.044

Source: Computed by author.

On the other hand, it was found that for domestic / service work, F-value= 2.40 and p-value = 0.091, suggesting the rejection of the null hypothesis, meaning the group means are statistically different. Finally, the F-ratio of 3.480 and p-value= 0.044 suggests the group means in this occupation are not identical, highlighting significant variability across groups. In summary, the result of ANOVA reveals that both domestic/service work and self-employed/small business occupation groups exhibit statistically significant differences.

A pair-wise comparison for occupational shifts in domestic /service work and self-employed/small business across different poverty groups has been represented in *Table 5*, using Tukey's post hoc test. However, the result for domestic or service work represented the comparison between chronic poor and poverty entry (0.050) and chronic poor and poverty escape (0.081) both statistically significant at 5% and 10 % significant level.

Table 5:Post-Hoc Tukey Test for Occupational Shifting in surveyed slums

Nature of Poverty		Chronic poor	Poverty Escape	Poverty Entry	Non-Poor
Domestic / Service Work					
Chronic poor	Mean	—	-17.3	-18.89	-11.81
	difference				
	p-value				
Poverty Escape	Mean	—	—	-1.59	5.5
	difference				
	p-value				
Poverty Entry	Mean	—	—	0.996	0.856
	difference				
	p-value				
Non-Poor	Mean	—	—	—	7.09
	difference				
	p-value				
Self-Employed / Small Business					
Chronic poor	Mean	—	8.55	-10.3	-10.087
	difference				
	p-value				
Poverty Escape	Mean	—	—	-18.9	-18.639
	difference				
	p-value				

Informal	3.705***	0	3.981	9.165	3.360***	0	1.829	4.891
Migration Status: (reference: Non-Migrant)								
Migrant	-3.989***	0	-6.162	-1.815	-2.216***	0.005	-3.78	-0.652
Dependency Ratio: (reference: 0-25 %)								
25-50	2.516***	0.008	0.649	4.383	1.455*	0.064	-0.087	2.997
50 and above	3.343***	0	1.737	4.949	1.548**	0.022	0.221	2.874
Physical Asset: (reference: No)								
Yes	-2.280***	0.003	-3.797	-0.764	-2.053***	0.002	-3.351	-0.755
Site of the slum: (reference: Core area)								
Peri urban	0.818	0.365	-0.95	2.585	-0.322	0.658	-1.75	1.105
Mixed developed	1.608	0.185	-0.223	3.44	0.9	0.254	-0.647	2.448
Constant	1.508	0.357	-1.698	4.714	2.047*	0.072	-0.183	4.276
Monthly family income	-0.001***	0	-0.001	-0.001	0.000***	0	-0.001	0
Post-COVID								
Level of Education of the HH Head: (reference: Illiterate)								
Primary	-1.805*	0.058	-3.669	0.06	-1.178	0.18	-2.901	0.545
Secondary	-3.320***	0.001	-5.258	-1.382	-1.770**	0.042	-3.479	-0.06
Higher Secondary	-3.471**	0.023	-6.467	-0.476	-3.069**	0.018	-5.613	-0.524
Graduation and above	-4.525***	0.003	-7.556	-1.493	-18.928	0.988	-2576	2538.5
Occupation: (reference: Formal)								
Informal	6.573***	0	1.668	5.741	3.250***	0	1.573	4.927
Migration Status: (reference: Non-Migrant)								
Migrant	-4.148***	0	-6.303	-1.992	-1.862**	0.021	-3.443	-0.28
Dependency Ratio: (reference: 0-25 %)								
25-50	-0.478	0.619	-2.362	1.405	-0.369	0.655	-1.988	1.25
50 and above	0.731	0.363	-0.845	2.306	0.21	0.77	-1.199	1.62
Physical Asset: (reference: No)								
Yes	-1.273*	0.086	-2.724	0.178	-1.438**	0.027	-2.712	-0.164
Site of the slum: (reference: Core area)								
Peri urban	1.666*	0.097	-0.3	3.631	0.971	0.284	-0.806	2.748
Mixed developed	-0.875	0.347	-2.698	0.948	0.057	0.947	-1.625	1.739
Constant	7.871***	0	4.385	11.356	3.534**	0.025	0.441	6.627

Pre-COVID-19: Log likelihood = -125.707, $\chi^2 = 383.39$, Pseudo R² = 0.604; **post-COVID-**

19: Log likelihood = -126.484, $\chi^2 = 391.29$, Pseudo R² = 0.6073

Note: Coef. = Coefficient of the multinomial logit model, CI = Confidence Interval, ***

Significant at 1%; ** Significant at 5%; * Significant at 10%.

Source: Computed by author.

The results indicated that the household monthly income was a significant determinant of poverty. The findings showed that there was a negative correlation between income level and poverty likelihoods (Coefficient = - 0.0009, $p = 0.000$; Coefficient = -0.0003, $p = 0.000$) for "poor" and "vulnerable non-poor" categories,

respectively during pre- and post-COVID-19. Educational level was also a critical factor in reducing poverty among the households living in slum areas. The model demonstrated that having a primary education significantly decreased the probability of being classified as poor or vulnerable non-poor in both timeframes (Coefficient = -1.582, $p= 0.061$, significant at 10 % level; Coefficient = -1.481, $p= 0.047$ significant at 5 % level). The coefficient values indicated a negative relationship between educational attainment and poverty risk, specifically, -2.776 ($p= 0.002$) for secondary and -4.050 ($p= 0.021$) for graduate education during the pre- and post-COVID-19 periods.

Employment in the informal sector was a dominant factor affecting household's poverty dynamics as there was a positive correlation between employment and poverty dynamics s (poor coefficient = 3.705, $p= 0.000$; vulnerable non-poor-coefficient= 3.360, $p= 0.000$) during pre-COVID-19 periods. There was a stronger association between employment in the informal sector and poverty dynamics i.e. 6.57 times more likely to be categorized as poor and 3.25 times more likely to be vulnerable non-poor. There was a stronger association between employment informal sectors and poverty dynamics during post-COVID-19 periods.

The migrant households showed a significant decrease of lower likelihood into the poor or vulnerable non-poor categories compared to non-migrant households with coefficient values of -3.988 and -2.216, respectively during the pre-COVID period. This pattern persisted even during the post-pandemic with migration decreasing the probability of poverty by 4.147 times. The households with a dependency ratio exceeding 50%, there was probability of being classified as poor increased by 3.342 times during pre-COVID-19 periods. The geographical location of households significantly affected the poverty dynamics, particularly during the post-COVID-19 periods. The results showed that the households residing in peri-urban areas were more likely to be classified as poor compared to those residing in core urban core areas.

4 Discussion

There were variations of the relative poverty across the slums. Sufalpally and Bhagabandhpara had the highest PGR indicating a significant income gap and escaping poverty due to their financial needs. These results indicated the fact that

these slum areas were characterized by heterogeneous income group households with diversified socio-economic conditions. Simuldanga and Sufalpally slums were characterized by high HCR and PGR revealing the dual issue of widespread and deep poverty among the households, and making these slums particularly vulnerable [60]. The higher HCR and PGR also revealed that these slums underscored the prevalence of poverty in these areas and its intensity, with many residents facing both widespread deprivation and significant income deficits[61]. The HCR and PGR also varied across the core, peri-urban or mixed development areas indicating the fact that there is a relation between poverty and the spatial distribution of households [62]. The HCR and PGR were the highest in Kasaimahalla, Deshbandhu road by lane, Simuldanga and Sufalpally slums again indicating that the households residing in these slums have high income inequality and gaps.

As per the results of the Gini coefficient, it was found that Deshbandhu Road by Lane and Bhagabandhpara had the highest value indicating inequality of income among the households living in these slums and limited access to employment opportunities or highly variable income sources among households in slums [63]. On the other hand, Simuldanga and Sekrapara had the lowest income inequality indicating equitable distribution because of better access to community resources, stable local employment opportunities, or greater economic support networks. The results also showed spatial variation of income inequality across the slums located in the core and peri-urban or mixed development areas. For example, the slums located in cores were characterized by relatively higher income inequality as compared to the slums located in the peri-urban or mixed development areas.

In the previous piece of the literature, it was well documented that poverty has been significantly affected by to emergence of COVID-19 [64]. In this study also, it was found that poverty conditions varied during pre- and post-COVID-19 periods. Over 50% of the households remained consistently poor in both pre- and post-COVID-19 periods in Sufalpally indicating the fact that there were limited opportunities towards socio-economic mobility [65,66]. Human mobility decreased during the COVID-19 pandemic due to strict government-imposed lockdowns, travel restrictions, and social distancing measures aimed at curbing the virus's spread[67,68]. Non-essential businesses, schools, and public spaces were closed, while work-from-home policies reduced commuting. Fear of infection also discouraged people from leaving their

homes. International and domestic travel bans further limited movement. Public transport use plummeted due to safety concerns, and recreational activities were curtailed. These restrictions disrupted daily routines, significantly reducing mobility across urban and rural areas. The pandemic underscored the critical role of mobility in socio-economic activities and its vulnerability during global health crises. However, despite the general persistence of poverty in Sufalpally is followed closely by Sekrapara, Simuldanga, and Kasaimahalla, approximately 24% of households in Sufalpally managed to transition out of poverty. Specifically, 16.67% shifted into the vulnerable non-poor category, and 7.14% attained the non-poor status. This upward mobility signals some resilience within the community, potentially due to targeted interventions or resourcefulness among certain households.

The results showed a decrease in the percentages of households engaged in manual labour or unskilled in Napitpara and Deshbandhu Road by Lane. The increase in people working in manual labour or unskilled jobs during the post-COVID-19 period was driven by widespread economic disruptions [69,70]. The pandemic caused job losses in formal sectors, particularly in service industries, tourism, and manufacturing, forcing many to seek informal or unskilled employment[71,72]. Migrant workers, who returned to their hometowns during lockdowns, often lacked access to skilled opportunities and relied on manual labour for income [73,74]. Economic recovery efforts created a demand for construction, logistics, and agriculture jobs, further attracting workers. Additionally, the need for quick income, coupled with limited skilling opportunities, pushed many into unskilled labour roles for survival. The engagement with the domestic sector dropped from pre- to post-COVID-19 periods due to significant shifts in economic conditions and lifestyle changes[75]. The pandemic led to widespread job losses and economic downturns, which impacted disposable incomes and reduced demand for domestic services [76]. Health concerns and social distancing measures also discouraged in-home services, altering how households managed chores and care giving. Post-pandemic, many households adapted to more self-sufficient routines or technology-assisted solutions, such as cleaning robots, reducing reliance on domestic help. Additionally, former domestic workers often shifted to other sectors or more stable jobs as economies began to recover and diversify post-COVID.

Poverty during the COVID-19 period was exacerbated by several interconnected socio-economic factors, disproportionately impacting vulnerable households. Monthly income was a significant determinant, as low-income households experienced a sharp decline in earnings due to job losses and restricted economic activities during lockdowns. Daily wage earners, particularly those in the informal sector, faced income volatility, leaving them unable to meet basic needs due to a lack of savings or formal financial support. Educational levels also played a crucial role, as households with lower education were more likely to rely on low-skilled jobs, which were among the first to be disrupted. This left less-educated workers with limited opportunities for alternative or remote employment. Employment in the informal sector further intensified poverty, as workers lacked job security, social protection, and access to unemployment benefits. The abrupt halt of informal economic activities left these households without any financial safety net. Migrant households were particularly affected, as many workers lost urban jobs and were forced to return to their native regions, incurring significant migration costs while losing income sources. The absence of formal support systems in rural areas compounded their vulnerability. Households with a high dependency ratio faced additional economic strain, as the loss of income from primary earners severely limited their ability to afford essentials like healthcare, education, and food. Furthermore, the location of slums contributed to heightened poverty levels, as overcrowded living conditions, inadequate sanitation, and limited access to healthcare made it harder for residents to maintain income-generating activities while also increasing their risk of infection. These factors collectively underscore how structural inequalities and pre-existing vulnerabilities were magnified during the pandemic, pushing already marginalized households further into poverty.

4.1 Limitations and future research directions

The main limitation of this study lies in its reliance on a monetary or unidimensional approach, which may fall short of capturing poverty's multifaceted nature. While monetary metrics offer valuable insights into regional microeconomic conditions, they overlook dimensions like health, education, and living standards that a multidimensional approach can reveal. Improvements in one aspect of a household do not necessarily translate into progress in others, underscoring the need for broader poverty metrics. Nonetheless, understanding the economic dimensions of

poverty is critical for addressing the immediate needs of disadvantaged populations and shaping informed policies. Notably, few studies focus on poverty dynamics at a micro level, often prioritizing larger units of analysis. This paper examines poverty status and its evolving dynamics over time within Purulia Municipality's slum areas, with particular emphasis on the impact of COVID-19. Such analysis could provide vital information for government bodies and policymakers to devise effective measures that mitigate poverty and help vulnerable populations withstand economic shocks.

4.2 Policy implications

In order to achieve the Sustainable Development Goals (SDGs), especially those that center on eradicating poverty (SDG 1), reducing inequality (SDG 10), and promoting sustainable cities and communities (SDG 11), it is imperative to evaluate the dynamics of poverty in slums both before and after COVID-19 (*Figure 7*). Due to overcrowding, a lack of essential facilities, and economic precarity, residents of urban slums faced increased hazards, which the COVID-19 pandemic greatly increased [77,78]. Designing focused solutions that support the SDGs requires an understanding of these dynamics. An evaluation offers vital information about the ways in which pandemic-induced shocks affected slum social mobility, health, education, food security, and income levels[79,80]. It draws attention to the differences in resilience strategies and resource availability between marginalized groups, highlighting the pressing need for inclusive policy. Furthermore, by determining which tactics were successful in lessening the pandemic's consequences, these assessments can help guide adaptive actions that will increase

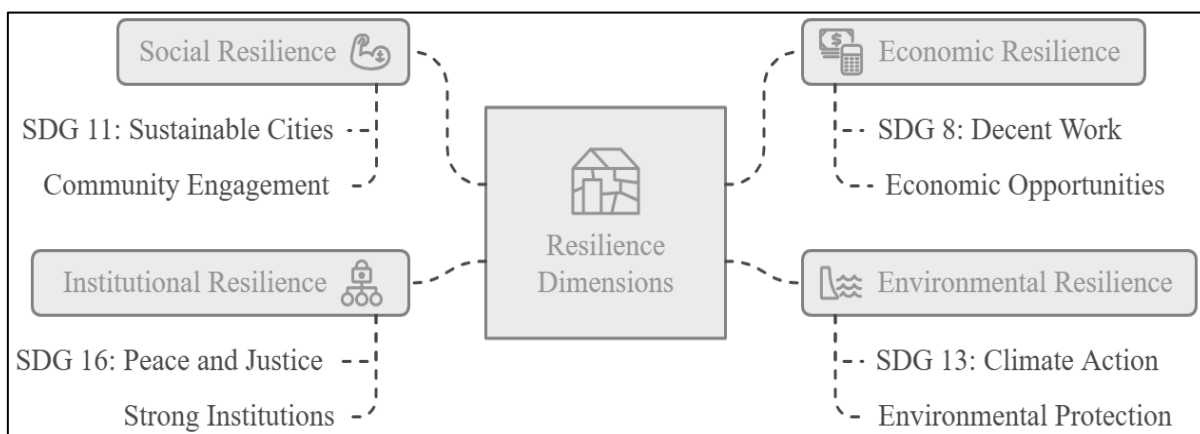


Fig. 7: Pathways to achieve resilience and SDGs in slums.

resilience in the future. Furthermore, advancing fairness in urban planning depends on these assessments. Assessments help create inclusive urban settings that promote the SDGs' "Leave No One Behind" principle by tackling the underlying causes of deprivation and improving access to basic amenities in slums [81].

To put it simply, analysing the dynamics of poverty in slums gives policymakers a data-driven basis on which to allocate resources, close socioeconomic divides, and create resilient urban systems, guaranteeing that the SDG targets are delivered efficiently and sustainably even in the face of upcoming global problems [82,83]. In order to achieve the SDGs and improve readiness for future pandemics, it is imperative to evaluate the dynamics of poverty in slums, particularly before and after COVID-19 [84,85]. The susceptibility of urban slum populations where hardship exacerbates inequality and restricts access to healthcare, education, and basic services was brought to light by the COVID-19 epidemic [35,86]. The foundation for identifying the main factors that influence vulnerability and resilience is provided by assessment. It aids in tracking the socioeconomic effects of crises that disproportionately affect slum inhabitants, such as food insecurity, job losses, and interrupted education. Policymakers can create focused interventions that improve healthcare and social safety nets and make them more accessible and inclusive by analysing the adaptive tactics used during COVID-19. Furthermore, thorough evaluations make it possible to spot weaknesses in the laws and infrastructure that are in place, which promotes the growth of resilient communities. The knowledge gained from these evaluations can help direct resource allocation and urban planning to lessen the vulnerability of slum inhabitants to pandemics and climate-related shocks in the future. Implementing the SDGs with these insights guarantees a fairer recovery and increases the resilience required to face new challenges. Assessments that put the needs of underserved groups first can accelerate the achievement of the SDGs and, in the end, promote an inclusive, sustainable, and pandemic-resilient urban future.

Table 7: Importance of assessment deprivation and resilience in slums in public health well-being

Aspect	Deprivation (current situation)	Resilience (desired outcome)	Relevance to SDGs and public health well-being
--------	---------------------------------------	------------------------------------	---

Access to Basic Services	Limited access to clean water, sanitation, electricity, healthcare, and education	Improved infrastructure, affordable healthcare, quality education, and clean energy	SDG 6 (Clean Water and Sanitation), SDG 7 (Affordable and Clean Energy), SDG 3 (Good Health and Well-Being). Access to these services improves overall health, education, and economic opportunities.
Health Outcomes	Poor sanitation, malnutrition, overcrowding, and limited healthcare access	Strong healthcare systems, nutritious food availability, and clean-living environments	SDG 3 (Good Health and Well-Being). Addressing health challenges helps reduce diseases, improve life expectancy, and increase quality of life, leading to better public health outcomes.
Economic Opportunities	Limited employment opportunities, low wages, informal economy reliance	Economic empowerment through job creation, skills training, and entrepreneurship	SDG 8 (Decent Work and Economic Growth). Creating economic opportunities helps reduce poverty, improve economic stability, and foster sustainable livelihoods in slum communities.
Environmental Conditions	Poor waste management, high pollution, inadequate green spaces	Sustainable urban planning, improved waste management, and green spaces	SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action). Sustainable environmental management promotes resilience to climate change, enhances urban livability, and mitigates pollution.
Social Inclusion	Social exclusion, inequality, and marginalization of vulnerable groups	Empowerment of marginalized groups, gender equality, and community solidarity	SDG 10 (Reduced Inequalities), SDG 5 (Gender Equality). Enhancing social inclusion and addressing inequalities improves overall community cohesion, resilience, and social justice.

Community Engagement	Lack of participation in decision-making processes	Active involvement of communities in planning, governance, and resilience-building	SDG 16 (Peace, Justice, and Strong Institutions). Engaging communities ensures that development plans reflect their needs and aspirations, enhancing social cohesion and governance effectiveness.
Climate Resilience	High vulnerability to climate hazards (e.g., floods, heatwaves)	Enhanced climate adaptation and disaster risk management	SDG 13 (Climate Action). Building climate resilience reduces vulnerability to environmental shocks and promotes long-term sustainability in slum areas.

814

815 The Indian government responded to the acute vulnerabilities of urban slums by
816 implementing focused efforts to reduce poverty during the COVID-19 pandemic [87].
817 Under the Pradhan Mantri Garib Kalyan Yojana (PMGKY), women with Jan Dhan
818 accounts received direct cash transfers, and farmers and the elderly received
819 assistance. To lessen the loss of daily pay, food security programs like the Pradhan
820 Mantri Garib Kalyan Ann Yojana (PMGKAY) and the expanded Public Distribution
821 System offered free rations. In order to supplement rural employment programs,
822 employment schemes, such as urban job initiatives under the Atmanirbhar Bharat
823 Abhiyan, provided temporary employment opportunities. Mobile testing and
824 immunization units, quarantine facilities, and the delivery of basic hygiene supplies
825 improved access to healthcare. The Pradhan Mantri Awas Yojana-Urban (PMAY-U)
826 housing projects sought to lessen overcrowding, which is a major contributor to the
827 spread of viruses. Food security for migratory workers between states was
828 guaranteed by the One Nation One Ration Card program, which also provided
829 transportation support to enable safe returns [88,89]. Long-term poverty reduction in
830 slums necessitates bolstering public health infrastructure and housing, as well as
831 expanding access to clean water, sanitation, and healthcare. Economic stability
832 depends on fostering livelihoods through skill development, career training, and
833 assistance for entrepreneurs [90]. Slum dwellers can be better prepared for future
834 shocks by increasing social safety nets like unemployment insurance and universal

health insurance [91]. In order to create equitable and sustainable urban environments, inclusive urban planning, which involves slum populations in decision-making, is essential. When combined, these diverse approaches can successfully combat urban poverty and advance social justice.

5. Conclusions

This study highlights the urgent need for targeted, multi-faceted policy interventions to alleviate poverty and improve living conditions in Purulia's slums. Key initiatives include enhancing access to essential services like sanitation, clean water, healthcare, and education, focusing on job security and livelihood programs, strengthening social inclusion programs, and enhancing education and skill development. Government schemes should expand service delivery infrastructure to ensure equitable access. Skill-based training and self-employment opportunities can empower slum residents to secure stable, higher-paying jobs, especially post-COVID-19. Social inclusion programs should integrate marginalized communities into mainstream social and economic programs, potentially through caste- and religion-sensitive initiatives. Expanding access to education and vocational training for both adults and children in slum areas is essential for building long-term resilience against poverty shocks. Assisting slum households in acquiring productive assets, such as housing and land rights, can offer economic resilience and reduce poverty persistence.

This study highlights the pressing need for policy frameworks that prioritize the unique socio-economic challenges in Purulia's slums, especially in the post-COVID-19 context. Persistent poverty and the socio-economic divide across slums emphasize the limitations of existing urban development schemes like the Pradhan Mantri Awas Yojana and Jawaharlal Nehru National Urban Renewal Mission, which, while beneficial, require improved implementation and resource allocation to be effective. The location of a slum plays a pivotal role in shaping poverty dynamics. This study highlights the need for location-specific slum upgrade programs to promote equitable development in the slums of Purulia Municipality. A participatory approach, involving local residents in poverty-alleviation efforts, can foster more inclusive and sustainable urban environments. By addressing these pressing challenges, policymakers can enhance social equity, ensure resource accessibility,

and facilitate a path out of chronic poverty for Purulia's marginalized urban communities.

Declarations

Funding

This study did not receive any external funding or financial support.

Credit authorship contribution statement:

Samyakami Kaibarta: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Somnath Mandal: Methodology, Data curation, Conceptualization. **Arijit Das:** Data curation, review & editing. **Manob Das:** Methodology, review & editing. **Suman Paul:** Review & editing, Supervision.

Declaration of competing interest:

The authors declare that there is no conflict of interest.

Ethical Approval

Ethics approval and compliance: The study was reviewed and approved by the Institutional Ethical Committee (IEC) of Sidho-Kanho-Birsha University, Purulia, West Bengal, India, at its meeting held on 7 May 2024 (Memo No. R/IEC/657/SKBU/24) with ethical clearance applicable to the research from 11 July 2022. The research was conducted in accordance with the ethical principles and institutional regulations governing research involving human participants, as prescribed by the Institutional Ethical Committee of Sidho-Kanho-Birsha University.

Consent to publish: Written informed consent for publication was obtained from all participants whose information was collected for this study. Participants were informed that the findings would be reported in an anonymised and aggregated form for academic and scientific publication.

Consent to participate: Written informed consent to participate in the study was obtained from all participants before data collection. The participants were informed about the purpose and nature of the study, the voluntary nature of their participation, and their right to decline participation or withdraw from the study without any adverse

consequences. Where participants were under 16 years of age, informed consent was obtained from their parent or legal guardian.

Data availability:

The datasets generated during and/or analysed during the current study are not publicly available due to privacy and confidentiality considerations related to the household-level survey data and ethical considerations, but are available from the corresponding author on reasonable request.

Reference

1. Khan I, Haleem A, Javaid M. Analysing COVID-19 pandemic through cases, deaths, and recoveries. *Journal of Oral Biology and Craniofacial Research*. 2020;10:450–69. <https://doi.org/10.1016/j.jobcr.2020.08.003>
2. Choudhury P, Ghosh RK, Sindhi S. COVID-19 Crisis, Pandemic Resilience and Linkages to Land: An Exposition. *SSRN Journal [Internet]*. 2020 [cited 2024 Nov 26]; <https://doi.org/10.2139/ssrn.3625042>
3. Duma Z, Chuturgoon AA, Ramsuran V, Edward V, Naidoo P, Mpaka-Mbatha MN, et al. The challenges of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) testing in low-middle income countries and possible cost-effective measures in resource-limited settings. *Global Health*. 2022;18:5. <https://doi.org/10.1186/s12992-022-00796-7>
4. Zhao SZ, Wong JYH, Wu Y, Choi EPH, Wang MP, Lam TH. Social Distancing Compliance under COVID-19 Pandemic and Mental Health Impacts: A Population-Based Study. *IJERPH*. 2020;17:6692. <https://doi.org/10.3390/ijerph17186692>
5. Goolsbee A, Syverson C. Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. *Journal of Public Economics*. 2021;193:104311. <https://doi.org/10.1016/j.jpubeco.2020.104311>

- 924 6. Saadat S, Rawtani D, Hussain CM. Environmental perspective of COVID-19.
925 Science of The Total Environment. 2020;728:138870.
926 <https://doi.org/10.1016/j.scitotenv.2020.138870>
- 927 7. SanJuan-Reyes S, Gómez-Oliván LM, Islas-Flores H. COVID-19 in the
928 environment. Chemosphere. 2021;263:127973.
929 <https://doi.org/10.1016/j.chemosphere.2020.127973>
- 930 8. Chirisa I, Mutambisi T, Chivenge M, Mabaso E, Matamanda AR, Ncube R. The
931 urban penalty of COVID-19 lockdowns across the globe: manifestations and lessons
932 for Anglophone sub-Saharan Africa. GeoJournal. 2022;87:815–28.
933 <https://doi.org/10.1007/s10708-020-10281-6>
- 934 9. Panneer S, Kantamaneni K, Akkayasamy VS, Susairaj AX, Panda PK, Acharya
935 SS, et al. The Great Lockdown in the Wake of COVID-19 and Its Implications:
936 Lessons for Low and Middle-Income Countries. IJERPH. 2022;19:610.
937 <https://doi.org/10.3390/ijerph19010610>
- 938 10. Dubois E, Yuan X, Bennett Gayle D, Khurana P, Knight T, Laforce S, et al.
939 Socially vulnerable populations adoption of technology to address lifestyle changes
940 amid COVID-19 in the US. Data and Information Management. 2022;6:100001.
941 <https://doi.org/10.1016/j.dim.2022.100001>
- 942 11. Li L, Taeihagh A, Tan SY. A scoping review of the impacts of COVID-19 physical
943 distancing measures on vulnerable population groups. Nat Commun. 2023;14:599.
944 <https://doi.org/10.1038/s41467-023-36267-9>
- 945 12. Blundell R, Costa Dias M, Joyce R, Xu X. COVID-19 and Inequalities*. Fiscal
946 Studies. 2020;41:291–319. <https://doi.org/10.1111/1475-5890.12232>
- 947 13. Rendon AFV, Volschan IM, Pereira MDN, Pimentel ADF, Monteiro WL, Oliveira
948 GMM. Marginalization, Vulnerability and Economic Dynamics in COVID-19.
949 International Journal of Cardiovascular Sciences. 2021;34:319–23.
950 <https://doi.org/10.36660/ijcs.20210029>
- 951 14. Sen D, Haldar S, Mandal S, Bhattacharya S, Paul S. Assessing urban inequality
952 from census data: a comparative analysis of proximate and non-proximate census

953 towns in West Bengal (India). *GeoJournal*. 2024;90:5.
954 <https://doi.org/10.1007/s10708-024-11240-1>

955 15. Von Seidlein L, Alabaster G, Deen J, Knudsen J. Crowding has consequences:
956 Prevention and management of COVID-19 in informal urban settlements. *Building*
957 *and Environment*. 2021;188:107472. <https://doi.org/10.1016/j.buildenv.2020.107472>

958 16. Wilkinson A, Ali H, Bedford J, Boonyabancha S, Connolly C, Conteh A, et al.
959 Local response in health emergencies: key considerations for addressing the
960 COVID-19 pandemic in informal urban settlements. *Environment and Urbanization*.
961 2020;32:503–22. <https://doi.org/10.1177/0956247820922843>

962 17. Workie E, Mackolil J, Nyika J, Ramadas S. Deciphering the impact of COVID-19
963 pandemic on food security, agriculture, and livelihoods: A review of the evidence
964 from developing countries. *Current Research in Environmental Sustainability*.
965 2020;2:100014. <https://doi.org/10.1016/j.crsust.2020.100014>

966 18. Gupta J, Bavinck M, Ros-Tonen M, Asubonteng K, Bosch H, Van Ewijk E, et al.
967 COVID-19, poverty and inclusive development. *World Development*.
968 2021;145:105527. <https://doi.org/10.1016/j.worlddev.2021.105527>

969 19. Manirambona E, Musa SS, Irakoze S, Uwizeyimana T, Gyeltshen D, Bizoza D, et
970 al. The impact of COVID-19 on international development aid and health systems
971 strengthening in low-income countries. *Annals of Medicine & Surgery [Internet]*. 2022
972 [cited 2026 Sept 8];82. <https://doi.org/10.1016/j.amsu.2022.104772>

973 20. Boro E, Stoll B. Barriers to COVID-19 Health Products in Low-and Middle-
974 Income Countries During the COVID-19 Pandemic: A Rapid Systematic Review and
975 Evidence Synthesis. *Front Public Health*. 2022;10:928065.
976 <https://doi.org/10.3389/fpubh.2022.928065>

977 21. Kassegn A. COVID-19: The impacts of the global crises on African remittances
978 and countries response to this an extreme crisis. McMillan D, editor. *Cogent*
979 *Economics & Finance*. 2021;9:1948665.
980 <https://doi.org/10.1080/23322039.2021.1948665>

- 981 22. Stevano S, Franz T, Dafermos Y, Van Waeyenberge E. COVID-19 and crises of
982 capitalism: intensifying inequalities and global responses. *Canadian Journal of*
983 *Development Studies / Revue canadienne d'études du développement*. 2021;42:1–
984 17. <https://doi.org/10.1080/02255189.2021.1892606>
- 985 23. Devereux S, Cuesta J. Urban-Sensitive Social Protection: How Universalized
986 Social Protection Can Reduce Urban Vulnerabilities Post COVID-19. *Progress in*
987 *Development Studies*. 2021;21:340–60. <https://doi.org/10.1177/14649934211020858>
- 988 24. Kesar S, Abraham R, Lahoti R, Nath P, Basole A. Pandemic, informality, and
989 vulnerability: impact of COVID-19 on livelihoods in India. *Canadian Journal of*
990 *Development Studies / Revue canadienne d'études du développement*.
991 2021;42:145–64. <https://doi.org/10.1080/02255189.2021.1890003>
- 992 25. Ashford NA, Hall RP, Arango-Quiroga J, Metaxas KA, Showalter AL. Addressing
993 Inequality: The First Step Beyond COVID-19 and Towards Sustainability.
994 *Sustainability*. 2020;12:5404. <https://doi.org/10.3390/su12135404>
- 995 26. Nwosu CO, Oyenubi A. Income-related health inequalities associated with the
996 coronavirus pandemic in South Africa: A decomposition analysis. *Int J Equity Health*.
997 2021;20:21. <https://doi.org/10.1186/s12939-020-01361-7>
- 998 27. Connor J, Madhavan S, Mokashi M, Amanuel H, Johnson NR, Pace LE, et al.
999 Health risks and outcomes that disproportionately affect women during the Covid-19
1000 pandemic: A review. *Social Science & Medicine*. 2020;266:113364.
1001 <https://doi.org/10.1016/j.socscimed.2020.113364>
- 1002 28. Hayes AR, Lee D. Women, work, and families during the COVID-19 pandemic:
1003 Examining the effects of COVID policies and looking to the future. *Journal of Social*
1004 *Issues*. 2023;79:1088–105. <https://doi.org/10.1111/josi.12510>
- 1005 29. Martin A, Markhvida M, Hallegatte S, Walsh B. Socio-Economic Impacts of
1006 COVID-19 on Household Consumption and Poverty. *EconDisCliCha*. 2020;4:453–79.
1007 <https://doi.org/10.1007/s41885-020-00070-3>
- 1008 30. Sharifi A, Khavarian-Garmsir AR. The COVID-19 pandemic: Impacts on cities
1009 and major lessons for urban planning, design, and management. *Science of The*

1010 Total Environment. 2020;749:142391.
 1011 <https://doi.org/10.1016/j.scitotenv.2020.142391>

1012 31. Bandarin F, Ciciotti E, Cremaschi M, Madera G, Perulli P, Shendrikova D. Which
 1013 Future for Cities after COVID-19 | An international Survey. SSRN Journal [Internet].
 1014 2020 [cited 2026 Sept 8]; <https://doi.org/10.2139/ssrn.3733709>

1015 32. Alam S, Adnan ZH, Baten MA, Bag S. Assessing vulnerability of informal floating
 1016 workers in Bangladesh before and during COVID-19 pandemic: a multi-method
 1017 analysis. *BIJ*. 2022;29:1677–702. <https://doi.org/10.1108/BIJ-06-2021-0329>

1018 33. Glover RE, Van Schalkwyk MCI, Akl EA, Kristjansson E, Lotfi T, Petkovic J, et al.
 1019 A framework for identifying and mitigating the equity harms of COVID-19 policy
 1020 interventions. *Journal of Clinical Epidemiology*. 2020;128:35–48.
 1021 <https://doi.org/10.1016/j.jclinepi.2020.06.004>

1022 34. Corburn J, Vlahov D, Mberu B, Riley L, Caiaffa WT, Rashid SF, et al. Slum
 1023 Health: Arresting COVID-19 and Improving Well-Being in Urban Informal
 1024 Settlements. *J Urban Health*. 2020;97:348–57. [https://doi.org/10.1007/s11524-020-](https://doi.org/10.1007/s11524-020-00438-6)
 1025 [00438-6](https://doi.org/10.1007/s11524-020-00438-6)

1026 35. Raju E, Dutta A, Ayeb-Karlsson S. COVID-19 in India: Who are we leaving
 1027 behind? *Progress in Disaster Science*. 2021;10:100163.
 1028 <https://doi.org/10.1016/j.pdisas.2021.100163>

1029 36. Buthelezi N, Leboto-Khetsi L, Nel V. Ending Extreme Poverty and Enhancing
 1030 Urban Health. In: Matamanda AR, Nel V, editors. *Sustainable Development Goals*
 1031 *and Urban Health* [Internet]. Cham: Springer Nature Switzerland; 2024 [cited 2026
 1032 Sept 8]. p. 13–31. https://doi.org/10.1007/978-3-031-68734-1_2

1033 37. Kaibarta S, Alam E, Saeed Al Hattawi K, Mandal S, Mandal P, Bhattacharya S, et
 1034 al. Analyzing morphologic dynamics in poor urban areas through earth observation:
 1035 The case of the Purulia, West Bengal, India. *Social Sciences & Humanities Open*.
 1036 2024;10:101123. <https://doi.org/10.1016/j.ssaho.2024.101123>

1037 38. Kaibarta S, Alam E, Saeed Al Hattawi K, Mandal S, Mandal P, Bhattacharya S, et
 1038 al. Analyzing morphologic dynamics in poor urban areas through earth observation:

1039 The case of the Purulia, West Bengal, India. *Social Sciences & Humanities Open*.
1040 2024;10:101123. <https://doi.org/10.1016/j.ssaho.2024.101123>

1041 39. Bhalerao S, Kadam P. Sample size calculation. *Int J Ayurveda Res*. 2010;1:55.
1042 <https://doi.org/10.4103/0974-7788.59946>

1043 40. Faber J, Fonseca LM. How sample size influences research outcomes. *Dental*
1044 *Press J Orthod*. 2014;19:27–9. <https://doi.org/10.1590/2176-9451.19.4.027-029.ebo>

1045 41. Kelley K, Maxwell SE, Rausch JR. Obtaining Power or Obtaining Precision:
1046 Delineating Methods of Sample-Size Planning. *Eval Health Prof*. 2003;26:258–87.
1047 <https://doi.org/10.1177/0163278703255242>

1048 42. BHAGAT RB. Emerging Pattern of Urbanisation in India. *Economic and Political*
1049 *Weekly*. 2011;Vol. 46:10-12 (3 pages).

1050 43. Kaibarta S, Mandal S, Mandal P, Bhattacharya S, Paul S. Multidimensional
1051 poverty in slums: an empirical study from urban India. *GeoJournal*. 2022;87:527–49.
1052 <https://doi.org/10.1007/s10708-021-10571-7>

1053 44. Jankowska MM, Weeks JR, Engstrom R. Do the most vulnerable people live in
1054 the worst slums? A spatial analysis of Accra, Ghana. *Annals of GIS*. 2011;17:221–35.
1055 <https://doi.org/10.1080/19475683.2011.625976>

1056 45. Mekasha TJ, Tarp F. Understanding poverty dynamics in Ethiopia: Implications
1057 for the likely impact of COVID-19. *Review Development Economics*. 2021;25:1838–
1058 68. <https://doi.org/10.1111/rode.12841>

1059 46. Mekasha TJ, Tarp F. Understanding poverty dynamics in Ethiopia: Implications
1060 for the likely impact of COVID-19. *Review Development Economics*. 2021;25:1838–
1061 68. <https://doi.org/10.1111/rode.12841>

1062 47. Dang HH, Lanjouw PF. Welfare Dynamics Measurement: Two Definitions of a
1063 Vulnerability Line and Their Empirical Application. *Review of Income and Wealth*.
1064 2017;63:633–60. <https://doi.org/10.1111/roiw.12237>

- 1065 48. Ram K, Yadav S. The Impact of COVID-19 on Poverty Estimates in India: A
1066 Study Across Caste, Class and Religion. *Contemporary Voice of Dalit*. 2024;16:86–
1067 100. <https://doi.org/10.1177/2455328X211051432>
- 1068 49. Rangarajan C, Mahendra Dev S. Poverty in India: Measurement, Trends and
1069 Other Issues. In: Hashim SR, Mukherji R, Mishra B, editors. *Perspectives on
1070 Inclusive Policies for Development in India* [Internet]. Singapore: Springer Nature
1071 Singapore; 2022 [cited 2026 Sept 8]. p. 255–84. [https://doi.org/10.1007/978-981-19-
1072 0185-0_13](https://doi.org/10.1007/978-981-19-0185-0_13)
- 1073 50. Datt G, Ravallion M. Has India's Economic Growth Become More Pro-Poor in the
1074 Wake of Economic Reforms? *The World Bank Economic Review*. 2011;25:157–89.
1075 <https://doi.org/10.1093/wber/lhr002>
- 1076 51. Park E, Nam S. Multidimensional poverty status of householders with disabilities
1077 in South Korea. *Int J Soc Welfare*. 2020;29:41–50. <https://doi.org/10.1111/ijsw.12401>
- 1078 52. Barder O. What is Poverty Reduction? *SSRN Journal* [Internet]. 2009 [cited 2024
1079 July 9]; <https://doi.org/10.2139/ssrn.1394506>
- 1080 53. Decerf B. Absolute and Relative Poverty Measurement: A Survey [Internet].
1081 World Bank, Washington, DC; 2022 [cited 2026 Sept 8].
1082 <https://doi.org/10.1596/1813-9450-10008>
- 1083 54. Nam S-J, Hwang H, Lee YL. Comparative study of poverty dynamics and income
1084 structure: Pre and post COVID-19 impact on households with and without disabilities
1085 in South Korea. *Disability and Health Journal*. 2024;17:101580.
1086 <https://doi.org/10.1016/j.dhjo.2024.101580>
- 1087 55. Alem Y, Beyene AD, Köhlin G, Mekonnen A. Modeling household cooking fuel
1088 choice: A panel multinomial logit approach. *Energy Economics*. 2016;59:129–37.
1089 <https://doi.org/10.1016/j.eneco.2016.06.025>
- 1090 56. Mperejekumana P, Li H, Wu R, Lu J, Tursunov O, Elshareef H, et al.
1091 Determinants of Household Energy Choice for Cooking in Northern Sudan: A
1092 Multinomial Logit Estimation. *IJERPH*. 2021;18:11480.
1093 <https://doi.org/10.3390/ijerph182111480>

- 1094 57. Dartanto T, Nurkholis. The determinants of poverty dynamics in Indonesia:
1095 evidence from panel data. *Bulletin of Indonesian Economic Studies*. 2013;49:61–84.
1096 <https://doi.org/10.1080/00074918.2013.772939>
- 1097 58. Silva-Laya M, D'Angelo N, García E, Zúñiga L, Fernández T. Urban poverty and
1098 education. A systematic literature review. *Educational Research Review*.
1099 2020;29:100280. <https://doi.org/10.1016/j.edurev.2019.05.002>
- 1100 59. Wamuthenya, Wambui R. Determinants of Employment in the Formal and
1101 Informal Sectors of the Urban Areas of Kenya. *African Economic Research*
1102 *consortium*; 2010; <https://publication.aercafricalibrary.org/handle/123456789/1218>
- 1103 60. Patel A, Joseph G, Shrestha A, Foint Y. Measuring deprivations in the slums of
1104 Bangladesh: implications for achieving sustainable development goals. *Housing and*
1105 *Society*. 2019;46:81–109. <https://doi.org/10.1080/08882746.2019.1622346>
- 1106 61. Ghosh R, Mondal P. Unveiling the Complex Facets of Poverty: Unidimensional
1107 and Multidimensional Insights from Rural Areas of Suri Sadar Sub-Division, Birbhum
1108 District, Eastern India. *Societies*. 2024;14:54. <https://doi.org/10.3390/soc14040054>
- 1109 62. Kisiała W, Rącka I. Spatial and Statistical Analysis of Urban Poverty for
1110 Sustainable City Development. *Sustainability*. 2021;13:858.
1111 <https://doi.org/10.3390/su13020858>
- 1112 63. Tripathi S. Determinants of Large City Slum Incidence in India: A Cross-Sectional
1113 Study: Large City Slum Incidence in India. *Poverty & Public Policy*. 2015;7:22–43.
1114 <https://doi.org/10.1002/pop4.93>
- 1115 64. Suryahadi A, Al Izzati R, Suryadarma D. Estimating the Impact of Covid-19 on
1116 Poverty in Indonesia. *Bulletin of Indonesian Economic Studies*. 2020;56:175–92.
1117 <https://doi.org/10.1080/00074918.2020.1779390>
- 1118 65. Gauvin L, Bajardi P, Pepe E, Lake B, Privitera F, Tizzoni M. Socio-economic
1119 determinants of mobility responses during the first wave of COVID-19 in Italy: from
1120 provinces to neighbourhoods. *J R Soc Interface*. 2021;18:20210092.
1121 <https://doi.org/10.1098/rsif.2021.0092>

- 1122 66. Nundy S, Ghosh A, Mesloub A, Albaqawy GA, Alnaim MM. Impact of COVID-19
1123 pandemic on socio-economic, energy-environment and transport sector globally and
1124 sustainable development goal (SDG). *Journal of Cleaner Production*.
1125 2021;312:127705. <https://doi.org/10.1016/j.jclepro.2021.127705>
- 1126 67. Girum T, Lentiro K, Geremew M, Migora B, Shewamare S, Shimbire MS. Optimal
1127 strategies for COVID-19 prevention from global evidence achieved through social
1128 distancing, stay at home, travel restriction and lockdown: a systematic review. *Arch*
1129 *Public Health*. 2021;79:150. <https://doi.org/10.1186/s13690-021-00663-8>
- 1130 68. Rahman SM, Ratrout N, Assi K, Al-Sghan I, Gazder U, Reza I, et al.
1131 Transformation of urban mobility during COVID-19 pandemic – Lessons for
1132 transportation planning. *Journal of Transport & Health*. 2021;23:101257.
1133 <https://doi.org/10.1016/j.jth.2021.101257>
- 1134 69. Koutroukis T, Chatzinikolaou D, Vlahos C, Pistikou V. The Post-COVID-19 Era,
1135 Fourth Industrial Revolution, and New Globalization: Restructured Labor Relations
1136 and Organizational Adaptation. *Societies*. 2022;12:187.
1137 <https://doi.org/10.3390/soc12060187>
- 1138 70. Vyas L. “New normal” at work in a post-COVID world: work–life balance and
1139 labor markets. *Policy and Society*. 2022;41:155–67.
1140 <https://doi.org/10.1093/polsoc/puab011>
- 1141 71. Mamgain RP. Understanding labour market disruptions and job losses amidst
1142 COVID-19. *J Soc Econ Dev*. 2021;23:301–19. [https://doi.org/10.1007/s40847-020-](https://doi.org/10.1007/s40847-020-00125-x)
1143 [00125-x](https://doi.org/10.1007/s40847-020-00125-x)
- 1144 72. Moore W, Pascal S. The determinants of job losses due to the COVID-19
1145 pandemic in small Island developing states. *Cogent Economics & Finance*.
1146 2024;12:2316333. <https://doi.org/10.1080/23322039.2024.2316333>
- 1147 73. Sengupta S, Jha MK. Social Policy, COVID-19 and Impoverished Migrants:
1148 Challenges and Prospects in Locked Down India. *The International Journal of*
1149 *Community and Social Development*. 2020;2:152–72.
1150 <https://doi.org/10.1177/2516602620933715>

- 1151 74. Srivastava R. Labour Migration, Vulnerability, and Development Policy: The
1152 Pandemic as Inflexion Point? *Ind J Labour Econ.* 2020;63:859–83.
1153 <https://doi.org/10.1007/s41027-020-00301-x>
- 1154 75. Ibn-Mohammed T, Mustapha KB, Godsell J, Adamu Z, Babatunde KA, Akintade
1155 DD, et al. A critical analysis of the impacts of COVID-19 on the global economy and
1156 ecosystems and opportunities for circular economy strategies. *Resources,*
1157 *Conservation and Recycling.* 2021;164:105169.
1158 <https://doi.org/10.1016/j.resconrec.2020.105169>
- 1159 76. Yu Z, Razzaq A, Rehman A, Shah A, Jameel K, Mor RS. Disruption in global
1160 supply chain and socio-economic shocks: a lesson from COVID-19 for sustainable
1161 production and consumption. *Oper Manag Res.* 2022;15:233–48.
1162 <https://doi.org/10.1007/s12063-021-00179-y>
- 1163 77. Akter S, Hakim SS, Rahman MdS. Planning for pandemic resilience: COVID-19
1164 experience from urban slums in Khulna, Bangladesh. *Journal of Urban Management.*
1165 2021;10:325–44. <https://doi.org/10.1016/j.jum.2021.08.003>
- 1166 78. Dubey S, Sahoo KC, Dash GC, Sahay MR, Mahapatra P, Bhattacharya D, et al.
1167 Housing-related challenges during COVID-19 pandemic among urban poor in low-
1168 and middle-income countries: A systematic review and gap analysis. *Front Public*
1169 *Health.* 2022;10:1029394. <https://doi.org/10.3389/fpubh.2022.1029394>
- 1170 79. Ramaiya A, Chandra-Mouli V, Both R, Gottert A, Guglielmi S, Beckwith S, et al.
1171 Assessing the health, social, educational and economic impact of the COVID-19
1172 pandemic on adolescents in low- and middle-income countries: a rapid review of the
1173 literature. *Sexual and Reproductive Health Matters.* 2023;31:2187170.
1174 <https://doi.org/10.1080/26410397.2023.2187170>
- 1175 80. Roy S, Shrestha KK, Sarkar OT, Singh A, Sultana R. Reframing urban
1176 informality: Gendered impacts of COVID-19 in Bangladeshi slums. *Progress in*
1177 *Disaster Science.* 2024;22:100317. <https://doi.org/10.1016/j.pdisas.2024.100317>
- 1178 81. Orkpeh AK, Adedire FM. African urban peripheries and informal development: A
1179 review of challenges and sustainable approaches to inclusive cities. *Norsk*

- 1180 Geografisk Tidsskrift - Norwegian Journal of Geography. 2024;78:40–53.
1181 <https://doi.org/10.1080/00291951.2024.2325446>
- 1182 82. Bachmann N, Tripathi S, Brunner M, Jodlbauer H. The Contribution of Data-
1183 Driven Technologies in Achieving the Sustainable Development Goals. Sustainability.
1184 2022;14:2497. <https://doi.org/10.3390/su14052497>
- 1185 83. Leal Filho W, Mbah MF, Dinis MAP, Trevisan LV, De Lange D, Mishra A, et al.
1186 The role of artificial intelligence in the implementation of the UN Sustainable
1187 Development Goal 11: Fostering sustainable cities and communities. Cities.
1188 2024;150:105021. <https://doi.org/10.1016/j.cities.2024.105021>
- 1189 84. Clemente-Suárez VJ, Rodriguez-Besteiro S, Cabello-Eras JJ, Bustamante-
1190 Sanchez A, Navarro-Jiménez E, Donoso-Gonzalez M, et al. Sustainable
1191 Development Goals in the COVID-19 Pandemic: A Narrative Review. Sustainability.
1192 2022;14:7726. <https://doi.org/10.3390/su14137726>
- 1193 85. Simon D, Arano A, Cammisa M, Perry B, Pettersson S, Riise J, et al. Cities
1194 coping with COVID-19: *Comparative perspectives*. City. 2021;25:129–70.
1195 <https://doi.org/10.1080/13604813.2021.1894012>
- 1196 86. Horne R, Willand N, Dorignon L, Middha B. Housing inequalities and resilience:
1197 the lived experience of COVID-19. International Journal of Housing Policy.
1198 2023;23:313–37. <https://doi.org/10.1080/19491247.2021.2002659>
- 1199 87. Auerbach AM, Thachil T. How does Covid-19 affect urban slums? Evidence from
1200 settlement leaders in India. World Development. 2021;140:105304.
1201 <https://doi.org/10.1016/j.worlddev.2020.105304>
- 1202 88. Schmidt-Sane M, Bhatt M, Pandya M, Mehta L. Gendered impacts on internal
1203 migrant workers in the informal economy in India. In: McAuliffe M, Bauloz C, editors.
1204 Research Handbook on Migration, Gender, and COVID-19 [Internet]. Edward Elgar
1205 Publishing; 2024 [cited 2026 Sept 8]. p. 83–94.
1206 <https://doi.org/10.4337/9781802208672.00012>

- 1207 89. Tumbe C, Jha RK. One Nation, One Ration, Limited Interstate Traction: Migration
1208 and PDS Portability in India. Urbanisation. 2024;9:87–103.
1209 <https://doi.org/10.1177/24557471241237098>
- 1210 90. Shkabatur J, Bar-El R, Schwartz D. Innovation and entrepreneurship for
1211 sustainable development: Lessons from Ethiopia. Progress in Planning.
1212 2022;160:100599. <https://doi.org/10.1016/j.progress.2021.100599>
- 1213 91. Singh J, Singh M. Does financial inclusion impact socio-economic stability? A
1214 study of social safety net in Indian slums. IJSE. 2023;50:1060–84.
1215 <https://doi.org/10.1108/IJSE-04-2022-0261>
- 1216

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Supplementary.docx](#)