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Beyond the Walls: Patterns of Child Labour, Forced Labour, and Exploitation in a New Domestic Workers Dataset

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Abstract: The new Domestic Workers Dataset is the largest single set of surveys (n = 11,759) of domestic workers to date. Our analysis of this dataset reveals features about the lives and work of this "hard-to-find" population in India—a country estimated to have the largest number of people living in forms of contemporary slavery (11 million). The data allow us to identify child labour, indicators of forced labour, and patterns of exploitation—including labour paid below the minimum wage—using bivariate analysis, factor analysis, and spatial analysis. The dataset also helps to advance our understanding of how to measure labour exploitation and modern slavery by showing the value of "found data" and participatory and citizen science approaches.

Keywords: forced labour; child labour; domestic workers; India; datasets; exploitation; minimum wage

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1. Introduction

Using India's Periodic Labour Force Survey, the International Labour Organisation (ILO) estimates the number of domestic workers in India as 4.764 million [1]. Globally, the ILO estimates that there are at least 67 million domestic workers over the age of 15 worldwide, 80% of whom are women [2], and that 7.1 million children globally are engaged in forms of domestic work that constitute child labour [3]. The ILO, Walk Free, and the International Organisation for Migration (IOM) estimate that 8% of all people in forced labour exploitation are domestic workers [4]: 1.4 million people, the majority female.

The ILO estimate of 4.764 million is likely an underestimate. The Women in Informal Employment: Globalizing and Organizing (WIEGO) network estimates the number at 5.235 million [5], other estimates have ranged from 2.5 to 90 million [6], and the Indian government's e-Shram portal, a National Database of Unorganized Workers launched in 2021 that aims to match individuals with relevant social security schemes, reported registrations of 28 million domestic and household workers across the country as of December 2023. The ILO estimate and other studies have confronted the problem that domestic work's hidden nature—informal and in private households—makes its extent and nature very difficult to establish. People in domestic labour are among the most challenging to survey. The ILO has explained that official statistics tend to undercount domestic workers (2011) and suggested that the challenges of surveying domestic workers require innovative surveying approaches, as some domestic workers may not know their activity is a form of employment, live in contexts where domestic work has social stigma, or have been trafficked into domestic work and so are deliberately hidden [7].

The informality and hidden nature of this work also contributes to the vulnerability of domestic workers. For example, in India, people in domestic labour have no legal protection as workers under the country's labour laws (which do not recognise domestic work *as* work) and have limited social protections [8]. Common working conditions include long and unregulated work hours, confinement, physical violence, sexual assault, and underpayment or no payment. Many people in domestic labour are from the most socially discriminated populations and have migrated to cities from poor rural areas or have been victims of human trafficking. Recruited to cities through offers of work, migrants are then victimised by labour agents who charge placement and travel fees that place workers in situations that meet the international definitions or indicators for trafficking (recruitment [etc.] through coercion or fraud for the purposes of exploitation [9]) and/or forced labour (e.g., deception, withholding of wages, debt bondage, abusive conditions [10]).

Part of an unregulated, informal sector, domestic workers are hidden from view behind the walls of private homes. However, the large number of respondents and regional geographic spread of a new Domestic Workers Dataset enables us to go "beyond the walls" of private households on a larger scale than ever before. The data let us analyse the circumstances of a hard-to-reach population whose lives are often hidden from view. In doing so, we have identified features of work that indicate forced and child labour, and we have established the levels of minimum wage non-compliance. After outlining methods and results, we discuss this new dataset's implications for understanding and measuring exploitation and forced labour in domestic work and for modern slavery measurement innovations more broadly.

2. Methods

2.1. Survey

Between 2015 and 2019, a network of Missionary Sisters of Mary Help of Christians (MSMHC) surveyed nearly 12,000 domestic workers across six states in Northeast India. MSMHC is the first indigenous Congregation in Northeast India (founded in 1942) and conducted this survey in order to generate baseline data for the impact assessment of a Centre for Development Initiatives (CDI) project that organises domestic workers into union structures. The survey respondents were domestic workers who registered with the Ferrando Domestic Workers Alliance (FDWA) as part of the CDI project.

The CDI is a front-line service provider to at-risk populations and a registered non-profit organisation. Based in Guwahati, the largest city in Assam (one of the states where the surveys were conducted), it works across all northeast states of India. Beginning in 2015, the CDI created pre-union groups that connect through the FDWA. It aimed to organise 30,000 domestic workers via these local groups and the FDWA across 12 cities: Agartala, Aizawl, Barpeta, Bongaigaon, Guwahati, Imphal, Kohima, Sarupathar, Shillong, Tezpur, Tinsukia, and Tura. By 2018, the CDI had identified 18,531 domestic workers in the 12 cities and had registered 13,668 with the FDWA into 534 groups. By 2019, over 18,000 workers were registered in more than 600 groups. Registration with the FDWA involved a payment by each worker of INR 10. The FDWA maintained a register of individuals, and each local group maintained a group register. The registered individuals received capacity-building support, rights training, and a platform for advocacy and campaigning.

Domestic workers completed the survey as they registered with the project's pre-union groups. Members of the CDI's network of Sisters conducted the interviews between 2015 and 2019 in the project's 12 cities. The interviews took place off-site from respondents' workplaces and in a one-to-one setting. The interviewers completed the surveys by hand. The surveys were stored in handwritten form until their digitization for this research (see Appendix A).

After receiving and cleaning the data, including duplicate identification, we identified a total of 11,759 respondents who were surveyed throughout six states of Northeast India (Assam, Manipur, Meghalaya, Mizoram, Nagaland, and Tripura). The surveys cover demographic characteristics, cultural factors, education status, and work background.

They contain information on both work history and current work, including terms of employment and working conditions. By using the ILO estimate of 4.764 million domestic workers and scaling for the total population in each of the cities surveyed, we calculate the survey had significant reach: it reached 6.95% of domestic workers.

2.2. Data Analysis

We completed correlation analysis, factor analysis, and spatial variation and state comparisons. The data are set in a geospatial context, with worker and employer addresses recorded. This enabled us to observe patterns and significant differences within and between the six states. For example, using the fine-scale geospatial data inherent in the dataset, we completed spatial mapping to examine the distribution of socio-demographic and cultural factors. Our analysis included examinations of how the quality of employment varies across geographical regions.

The data analysis stages were as follows:

1. Data cleansing, including duplicate identification, anomaly detection, and text coding;
2. General statistical analysis organised by category: socio-demographics (including family demographics), occupational information, employer information, terms of employment, working conditions, and social security;
3. Analysis of variable inter-relationships via correlation analysis to establish underlying and explanatory themes within the data;
4. Geospatial analysis of the dataset to show how key variables are distributed;
5. Examination of how the geospatial patterns and themes established in Stage 4 are distributed, with a focus on child labour;
6. Establishment of target “concept” variables (likely a proxy for “quality of working/employment situation”) and refinement of hypotheses (age, salary, and working hours were variables of interest).

As the survey respondents were not randomly selected, the data cannot be considered representative of the general population of domestic workers in Northeast India. For example, the average age of respondents is 36 (standard deviation [SD] 12), the average age when starting work is 26 (SD 10), and the mean number of children that each domestic worker has is 1 (SD 1). This may instead reflect the demographics of the respondents (those who chose to participate in the CDI empowerment programme).

In the full dataset collected from the surveys, no missing data were reported for 30 variables, while 86 variables had at least one missing data point. The missing data are most often found for variables providing space for (i) additional responses or reasons related to the previous question; (ii) shift times; and (iii) family members, which many respondents did not use. There also are missing data points for answers that depend on a positive response to a previous answer. For example, for any response to be relevant to the question “reason for salary deduction”? the respondent must have answered yes to the question “do you have any salary deductions”?

3. Results

3.1. Descriptive Statistics

The continuous and categorical variables included in the surveys are summarised in Tables 1 and 2. The mean respondent age was 36.5 (4–95, SD = 11.69) with mean numbers of family members and children of 2.6 (0–5, SD = 1.58) and 1.1 (0–5, SD = 1.15), respectively. Of the respondents, 91 (0.8%) were under the age of 14 and therefore classed as children for the purposes of work under the Child and Adolescent Labour (Prohibition and Regulation) Act, 1986.

Table 1. Continuous variables in the survey. The table includes the mean, minimum, maximum, and standard deviation values for each and the total number of respondents for which data are available (*n*).

Variable	Mean	Minimum	Maximum	Standard Deviation	*n*
Age	36.5	4	95	11.70	11,756
Number of Family Members	2.6	0	5	1.58	11,759
Number of Children	1.1	0	5	1.15	11,759
School Standard	6.6	0	13	2.85	5101
Age Started Work	26.5	1	80	10.27	11,758
Number Years Working	10.0	0	64	9.30	11,759
Number Previous Workplaces	1.4	0	29	1.78	11,759
Present job since	4.9	1	40	5.44	7822
Monthly Salary	₹3417.30	₹0	₹250,000	6803.76	11,759
Extra Allowance	₹260.0	₹10	₹5000	435.82	541
Number Hours Worked	6.2	0.5	24	3.06	11,747
Number Social Security	0.02	0	3	0.18	11,759

Table 2. Categorical variables in the survey. The most frequently occurring response is indicated (mode), along with the percentage of respondents who gave that response (%) and the total number of respondents for which data are available (*n*).

Variable	Mode	%	*n*
Sex	Female	99.3	11,759
Caste	OBC	33.9	11,759
Religion	Hinduism	60.0	11,759
Marital Status	Married	73.4	11,759
Attended School	Did Not	56.5	11,759
School Type	Government	93.4	5115
School Expense Paid	Self	61.7	5115
Reason Discontinued Studies	Poverty	73.5	5115
Reason for Changing Jobs	Financial	87.5	6484
Purpose of Work	Working Livelihood	94.0	11,759
Employment Type	Part time	66.4	11,759
Work Contract?	No	67.5	11,759
Contract Type	Oral	98.9	3821
Payment Frequency	Monthly	93.0	11,759
Salary Deductions?	No	92.0	11,759
Reason for Salary Deduction	Leave Taken	85.0	944
Extra Allowance?	No	95.4	11,013
Weekly Holiday	No	62.6	11,759
Annual Leave	No	63.0	11,759
Annual Leave Pay	Without Pay	50.6	4355
Tasks	Cleaning	82.1	11,697
Access to Medical Facilities?	No	74.4	11,759
Social Security Type	BPL	54.3	230

Nearly all respondents identified as female (99.3%) (Figure 1a). Most were married (73.4%) with fairly even numbers of widowed (13.4%) or single (10.9%) respondents (Figure 1d). The majority of respondents identified their religion as Hinduism (60.0%), with Christianity (28.6%) and Islam (10.6%) the second two most common religions. The remaining 0.8% of respondents were split between other religions (seventy-two respondents), Sikhism (twelve respondents), Buddhism (four respondents), and Jainism (one respondent) (Figure 1c). The most common caste represented was Other Backward Class (OBC, 33.9% of respondents), followed by Scheduled Tribes (STs) and Scheduled Castes (SCs) (26.4% and 25.1%, respectively) and General (14.6%) (Figure 1b). OBC is the term used in the Sisters' survey and is a collective term used by the Government of India to classify castes which are educationally or socially disadvantaged. It is one of several official classifications of the population of India, along with SC and ST. As socially marginalised and disadvantaged groups, SC, ST, and OBC are distinguished from each other in our analysis and as against the four "forward" castes of Brahmin, Kshatriya, Vaishya, and Shudra.

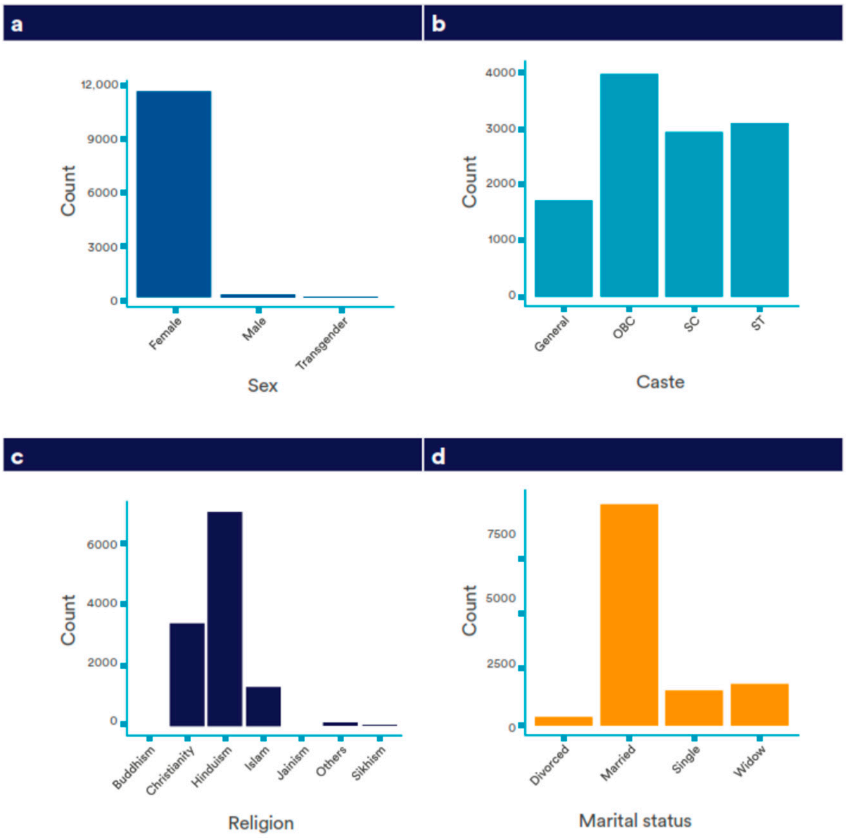

Figure 1. Personal information. All respondents' (**a**) sex, (**b**) caste, (**c**) religion, and (**d**) marital status (n = 11,759).

Of the 11,759 respondents, 43.5% did and 56.5% did not attend school. Of those who did (n = 5115), the vast majority attended government rather than private schools (93.4% vs. 6.6%). The expense of attending school was met, for the majority of respondents, by themselves (61.7%). Guardians or employers met the expenses for 32.3% and 5.9% of respondents, respectively (Figure 2a). The most common reason for discontinuing education was poverty (73.5% of respondents), followed by not being interested (14.1%) and death of parents (7.0%) (Figure 2b). The reason of "death of parents" points to economic constraints due to the loss of financial support. The remaining respondents listed "Any Other Reason" for leaving school, with around half (45.3%) providing further details, and 82.3% of these respondents identified marriage as the reason for leaving education, while 8.1% identified sickness.

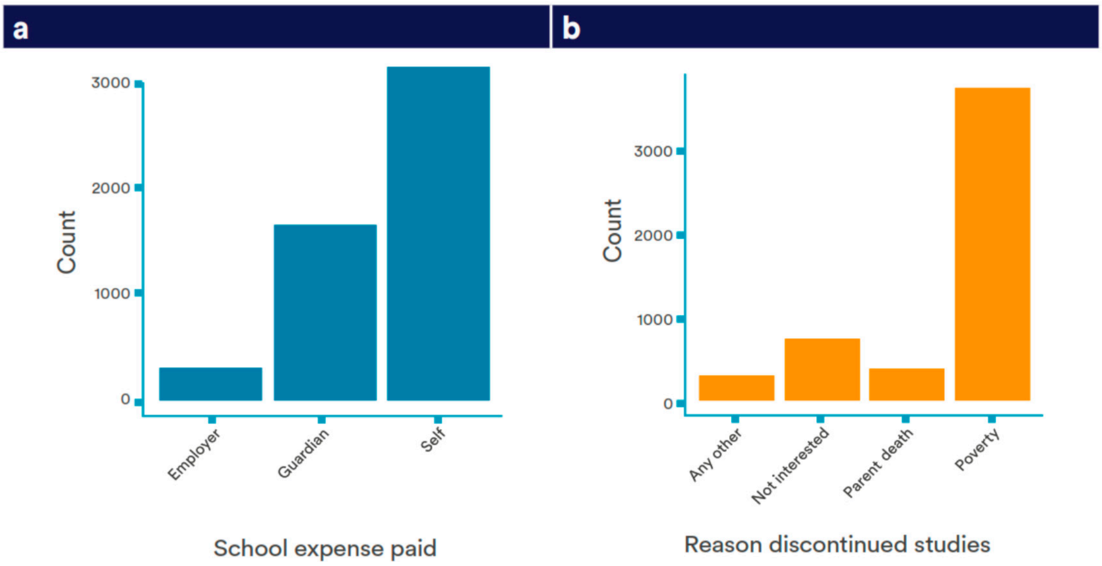

Figure 2. Information on school attendance. For respondents who attended school (n = 5115), responses on (**a**) who was responsible for meeting the schooling expense of the respondent and (**b**) the reason the respondent discontinued their studies.

Of those who did attend school, only 0.1% of respondents did not give further details on the level of school education obtained. For the rest, their school standard is measured on a scale from 0 to 13. This scale covers Pre-Primary (0), Lower Primary (1–4), Upper Primary/Middle School (5–8), Secondary (9–10), Senior/Higher Secondary (11–12), and University/Higher (13) education. The mean school standard for respondents was 6.6 (0–13, SD = 2.85, n = 5100) with Upper Primary/Middle School levels 5–8 the most common school standard obtained (44.1% of respondents) (Figure 3). The data therefore show a general trend in low educational attainment that ceases at Primary and Middle School level, with poverty as the main driver for school dropout rates.

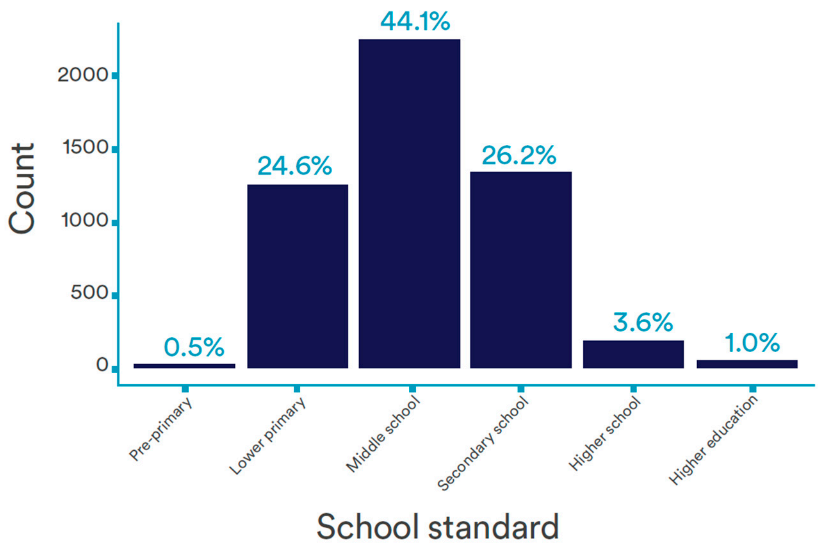

Figure 3. Educational levels. As obtained by respondents who attended school (n = 5101).

The mean age for starting work for the respondents was 26.5 (1–80, SD = 10.27), but 816 people (6.4% of respondents) began work when younger than 14 (Figure 4). The mean number of years working was 10.0 (0–64, SD = 9.30) with a mean number of previous workplaces of 1.4 (0–29, SD = 1.78).

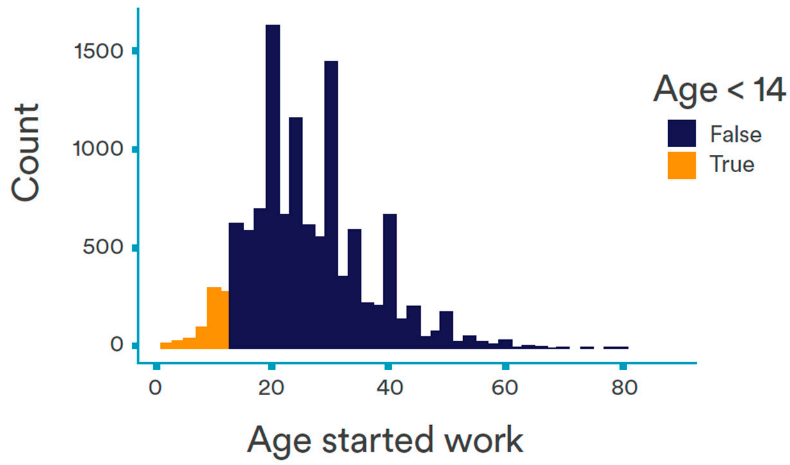

Figure 4. Work history. The age at which respondents started work (*n* = 11,755). Any respondents aged 14 or over (*n* = 10,939) are shown in grey. Respondents who started work aged below 14 years of age (*n* = 816) are shown in orange.

Of the total 11,759 respondents, 3981 (33.9%) had never changed jobs and had no previous workplace. Of those that had changed jobs (*n* = 7778), 66.1% gave reasons for this. The top five reasons were as follows:

7. Financial (respondents were in poverty and looking for a better wage): 87.5%;
8. Geographical (their or their employer's address changed): 3.1%;
9. Family/personal problems: 2.3%;
10. Marriage: 1.2%;
11. Illness: 0.9%.

Other reasons given (by <0.4% of respondents) included (i) pregnancy or caring for small children; (ii) termination of previous job by employer; (iii) behaviour of the employer (not paying wages on time); (iv) behaviour of the employer (cruel/strict); and (v) death of a family member.

The respondents were asked to identify the purpose of work from three options. Respondents were able to select multiple purposes, so percentages do not add up to 100. Working livelihood was selected by 94% of respondents. Supporting parents and working for education were identified as purposes behind work by 3.6% and 4.6% of respondents, respectively. The mean number of years respondents had held their current job was 4.9 (1–40, SD = 5.44). Of all 11,759 respondents, 66.4% identified their employment as part-time. The 33.6% who were full-time were live-in domestic workers. Only 32.5% of respondents had work contracts, and of these, only 1.1% were written. The mean monthly salary reported was INR 417.30/GBP 36.53 (INR 0/GBP 0–INR 250,000/2672.16, SD = 6803.76). Most respondents were paid monthly (93%) with no salary deductions (92%). Respondents who did experience salary deductions were asked to select the reason for this from four options, the most common being (i) leave taken (*n* = 803), followed by (ii) any other (*n* = 94) and (iii) things broken (*n* = 93). Only two respondents who selected "any other" provided further reasons, both being "illness". Only 541 respondents (4.6%) received extra allowance, the value of which ranged from INR 10/GBP 0.11 to INR 5000/GBP 53.45 (mean = INR 260.0/GBP 2.78, SD = 435.82). The majority of respondents received no weekly holiday (62.6%) and no annual leave (63.0%), and where annual leave was given, it was evenly split between paid or unpaid leave.

Respondents were asked to identify the tasks that they undertook during their work (Figure 5). The most common were cleaning (*n* = 9653, 82.1%), washing (*n* = 9436, 80.2%), and cooking and kitchen work (*n* = 6030, 51.3%). The average number of hours worked by respondents was 6.2 (0.5–24, SD = 3.06).

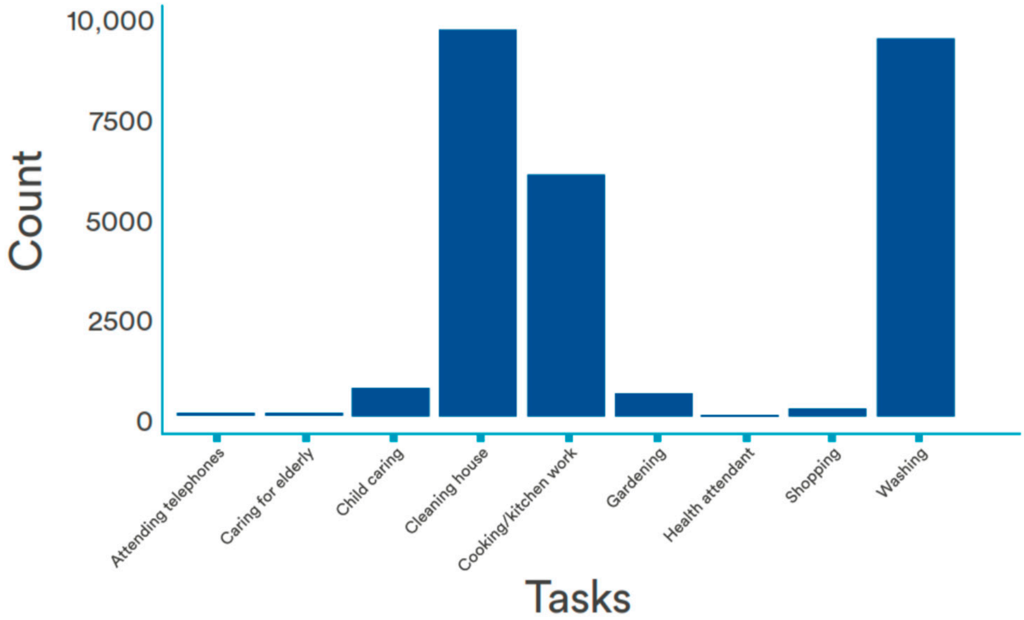

Figure 5. Main tasks of work. Respondents were able to identify more than one task, so the total numbers of people undertaking each task do not equal the number of respondents who gave details on this (n = 11,697).

The majority of respondents had no access to medical facilities (74.4%), and only 230 respondents (2%) had any level of social security in place. Of a potential list of social security types, respondents were asked to select which they had (Figure 6). The maximum number of social security schemes held by any one person was three (0–3, mean = 0.02, SD = 0.18), the most common being a Below Poverty Line (BPL) card that gives entitlements to food subsidies and other provisions (54.3%).

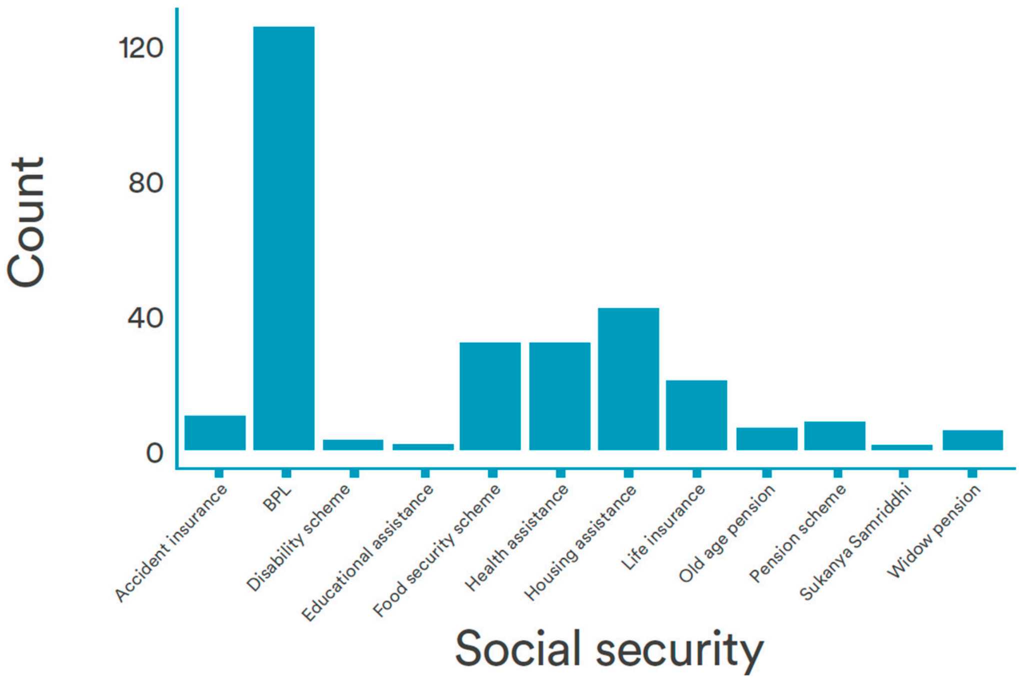

Figure 6. Social security scheme access. Respondents were able to select more than one social security scheme if they had multiple in place, so the counts for each social security scheme do not equal the total number of respondents who had social security in place (n = 230).

3.2. Variable Inter-Relationships

To establish underlying and explanatory themes within the data, we examined numerical variable inter-relationships through correlation analysis. Prior to analysing a subset of the variables, we conducted correlation analysis of all variables to establish inter-correlations in the dataset. These variables were removed from the subsequent correlation analysis to aid the interpretability of results (Figure 7).

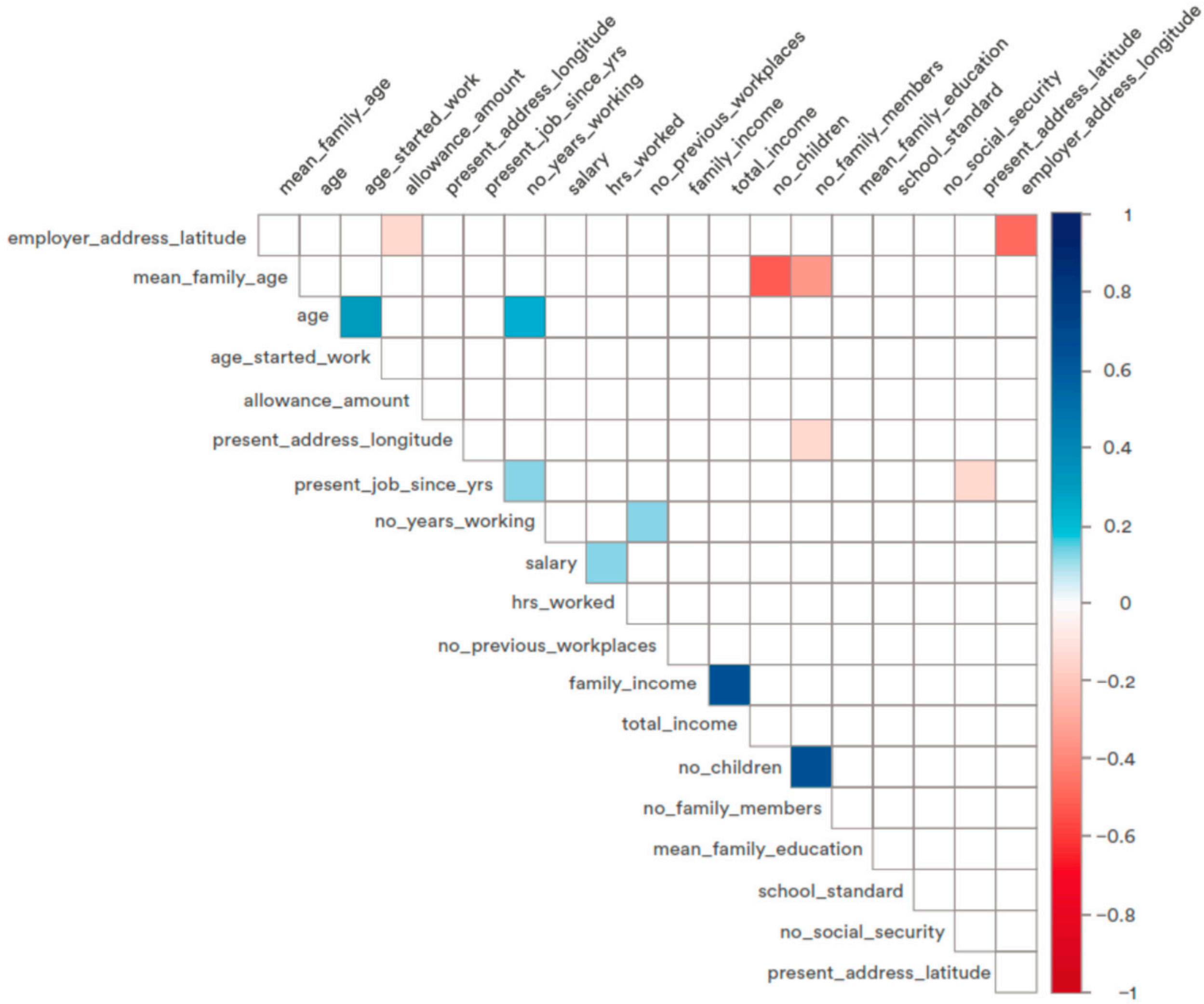

Figure 7. Correlation analysis results. The results in blue indicate positive relationships, and those in red indicate negative relationships. The gradient of colour indicates the strength of the relationship (darker = higher r^2). Only correlations that achieved statistical significance are shown. Correlations that were not significant ($p > 0.05$) are blank.

The variables removed include multiple replicates of variables for individual family members (i.e., family age, family education, and family income). These variables are summarised with "mean family age", "mean family education level", "number of children in the family", "number of family members", and "family income". This "family income" variable is combined with the respondent's "salary" to produce a "total income" variable.

The correlation analysis is further detailed in Table 3, where we suggest a rationale for each correlation. The table includes correlations relating to age, hours worked, and years in current job.

Table 3. Key correlations. The two variables comprising each correlation are named. The r^2 of the correlations and possible indications are noted. Potentially important correlations are highlighted (green).

No.	Variable	Variable 2	r^2	Details
1	Family income	Total income	0.86	An obvious correlation: the higher the income earned by family members (excluding the respondent), the higher the total income when including the respondent's income.
2	No children	No family members	0.80	An obvious correlation: the higher the number of children, the higher the number of family members.
3	Age	Age started work	0.63	The higher the respondent age, the higher the age of the respondent when starting work. This implies older respondents started work later in their lives. This may indicate recall bias or may indicate that the age of starting work was older in the past.
4	Mean family age	No children	−0.58	An obvious correlation: the higher the mean family age, the lower the number of children as a higher number of children will necessarily decrease the mean family age.
5	Age	No years working	0.51	An obvious correlation: the higher the respondent age, the higher the number of years working. A greater age indicates to more years available to have been working.
6	Employer address latitude	Employer address longitude	−0.49	An unimportant correlation: the higher the employer address latitude, the lower the employer address longitude. A by-product of the spatial patterning in the data.
7	Present job since (years)	Number years working	0.40	The longer the respondent has been in their present job, the longer they have been working. This potentially indicates that respondents are more likely to change jobs more frequently at the beginning of their career and retain the same job for longer periods later. Potentially this could be related to changing jobs in pursuit of better wages and/or because of life changes (marriage/relocating) which happen less often later in life (equivalent to a greater number of years working).
8	No years working	No previous workplaces	0.35	An obvious correlation: the more years you have been working, the higher number of previous workplaces. This seems related to the previous correlation.
9	Salary	Hours worked	0.33	The higher the respondent's salary, the greater the number of hours worked by the respondent. This makes logical sense, and may indicate that, for some people, a fair equivalency of increased hours equates to an increased salary is being worked out. The relatively low r^2, however, indicates that for many people, the number of hours worked does not have a strong bearing on their salary.
10	Mean family age	No family members	−0.33	An obvious correlation: the higher the mean family age, the lower the number of family members. This is related to correlation 4 (above). Number of family members is increased by increased numbers of children which reduces mean family age.
11	Employer address latitude	Allowance amount	−0.27	As latitude decreases, allowance amount increases. This potentially indicates that allowance amounts are higher in the south of the region covered by the surveys. This low r^2, however, may indicated this relationship only holds for few respondents.
12	Present address longitude	No family members	−0.19	As longitude increases, the number of family members decreases. This potentially indicates that there are fewer family members in families living in the east of the region covered by the surveys. This low r^2, however, may indicated this relationship only holds for few respondents.
13	Present job since (years)	Present address latitude	−0.18	As the number of years a respondent has held their current job increases, the latitude of their present address decreases. This potentially indicates that people work for longer in one place in the south of the region covered by the surveys. This low r^2, however, may indicated this relationship only holds for few respondents.

3.3. Identification of Key Features in the Dataset

We used non-negative matrix factorisation (NMF) analysis to extract seven key features from the dataset and to indicate which variables contribute to these features (Figure 8). NMF is a group of algorithms based on analysing the dataset as matrices. NMF has become a widely used tool for the analysis of high-dimensional data, as it automatically extracts sparse and meaningful features from a set of data vectors.

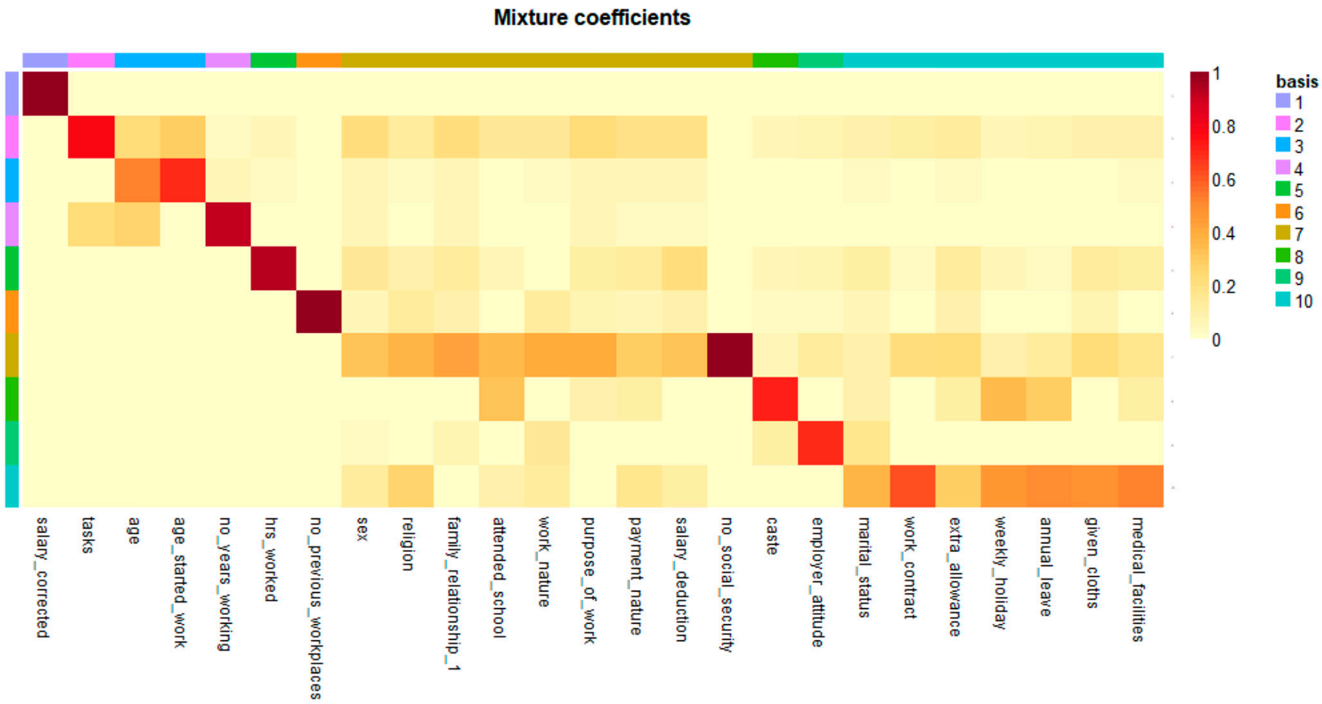

Figure 8. NMF output. The figure shows the seven key bases for the dataset. The bases are indicated by the colour ramp at the top and left of the figure. All of the variables upon which the NMF analysis was carried out are identified along the bottom of the figure. The colour ramp from red to yellow shows the strength of the relationship between each variable and the bases (darker red = stronger, lighter yellow = weaker).

The key features identified from the NMF analysis were salary, tasks, working hours, age of the respondent (at the time of survey and when starting work), and number of years working. These are the most easily interpreted features and are analysed with respect to spatial variation in the next section.

3.4. Spatial Variation and State Comparisons

The 11,759 respondents surveyed were located across six states in Northeast India: Assam, Manipur, Meghalaya, Mizoram, Nagaland, and Tripura (Figure 9). The number of respondents was not equally spread across the states, with Assam having the highest number (n = 7453), followed by Meghalaya (n = 2194), Manipur (n = 766), Tripura (n = 603), Nagaland (n = 374), and Mizoram (n = 369).

We examined how the key factors from the survey varied in a geospatial context. The tasks undertaken by respondents were fairly consistent across the states: cleaning, cooking and kitchen work, and washing (Figure 10). However, there were differences in ages, salaries, and number of hours worked (Table 4). For example, there was a statistically significant difference in mean salary across the six states in the region surveyed (one-way ANOVA: $p < 0.05$). Mizoram had the highest mean salary at INR 3427.0, and Nagaland had the lowest mean salary at INR 1763.0 (Table 5). There also was a statistically significant difference in the mean number of hours worked across the six states (one-way ANOVA: $p < 0.001$). Mizoram had the highest number of hours worked at 13.0 (Table 6).

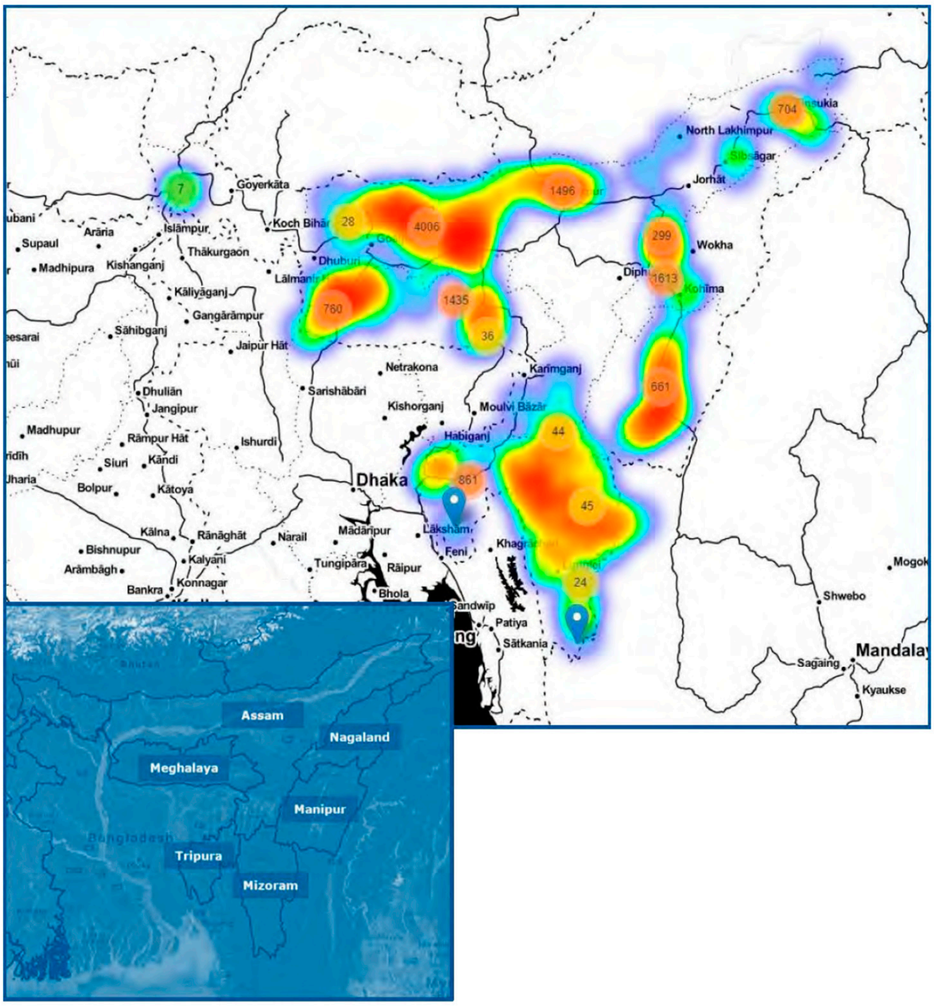

Figure 9. Heat map of the surveying region. The map shows the six surveyed states in India: Assam, Manipur, Meghalaya, Mizoram, Nagaland, and Tripura. The colour ramp indicates the number of respondents in certain areas (blue = fewer respondents, red = more respondents) with numbers of respondents for aggregated areas indicated. The state boundaries are depicted with dashed black lines. To enable better identification of the states, the inset shows the same region with state boundaries marked through solid black lines and the states named.

Table 4. State differences in ages, hours worked, and salary.

	Number of Responses	Mean Age (SD)	Mean Age When Started Work (SD)	Number of Hours Worked (SD)	Mean Salary (SD)
Assam	7453	38 (11)	28 (10)	6 (3)	2284 (3656)
Manipur	766	39 (11)	29 (10)	6 (3)	3404 (1391)
Meghalaya	2194	36 (11)	22 (9)	6 (3)	2900 (1653)
Mizoram	369	22 (6)	19 (5)	13 (3)	3427 (886)
Nagaland	374	22 (10)	18 (9)	7 (2)	1763 (3039)
Tripura	603	39 (11)	29 (10)	5 (3)	2306 (1386)

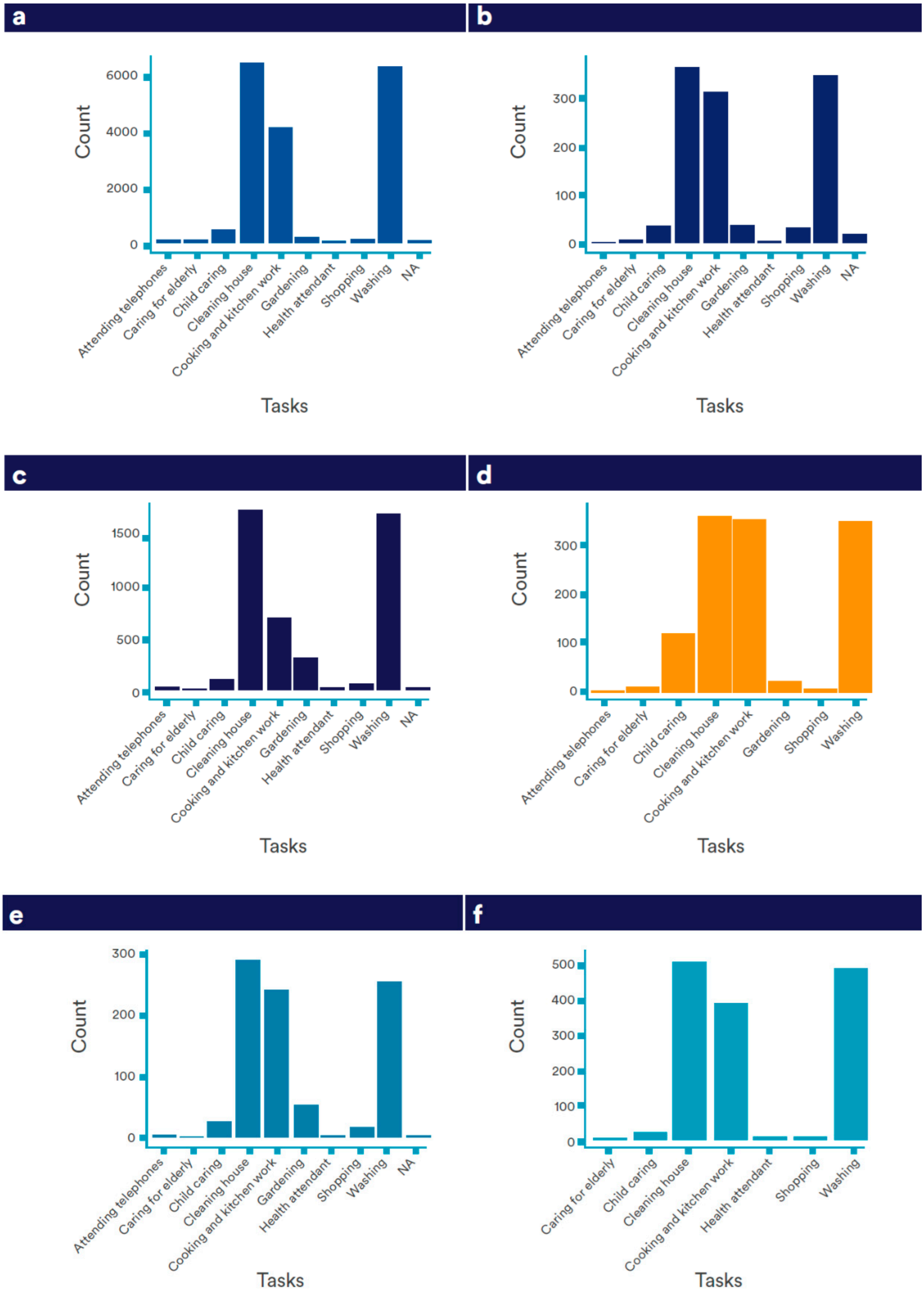

Figure 10. Main tasks by state. The tasks that respondents undertake are shown for (**a**) Assam; (**b**) Manipur; (**c**) Meghalaya; (**d**) Mizoram; (**e**) Nagaland; and (**f**) Tripura.

Table 5. Deviation in salary. The mean and standard deviation (SD) of the salary received by the respondents across the six states.

State	Mean	SD
Assam	2284.4	3655.9
Manipur	3403.9	1390.6
Meghalaya	2899.9	1652.8
Mizoram	3427.0	886.4
Nagaland	1763.0	3038.9
Tripura	2306.4	1386.4

Table 6. Deviation in working hours. The mean and standard deviation (SD) of the number of hours worked daily by the respondents.

State	Mean	SD
Assam	6.0	2.8
Manipur	6.2	2.5
Meghalaya	6.2	2.9
Mizoram	13.0	3.1
Nagaland	6.5	2.1
Tripura	4.6	2.8

We completed additional analysis of the data on salaries (Table 5) and daily hours worked (Table 6) to establish the rate of minimum wage non-compliance in the six states. To calculate hourly wages for individual respondents, we removed 830 respondents who had indicated receiving their salary daily, weekly, quarterly, or annually, leaving 10,929 who indicated receiving salaries monthly. This is because the survey asked "how much salary do you receive" and "when do you get salary", but it was not clear that all respondents answered these as two interdependent questions. Salaries are most commonly reported on a monthly basis in India [11,12], so respondents may have understood these as distinct questions and given their monthly salary rate but then described how often they receive any payment (e.g., each day or once a quarter). This seems likely because many salary rates given by those answering daily/weekly or quarterly/annually would be impossibly high or low, respectively, if it was really a daily/weekly or quarterly/annual rate. Potential anomalies in salary rates were far fewer for the respondents who indicated they are paid monthly. As it is not possible to establish how respondents understood the questions (i.e., as interdependent or separate), it would be risky to convert all salary rates to monthly, so we instead opted to only examine salary levels for respondents who indicated receiving wages monthly.

To establish an hourly rate, we also accounted for how many days off respondents had per week. Only 4500 respondents indicated they had time off each week and were not asked a follow-up question about how much time. For these respondents, we presumed a working week of six days. This is because India's Code on Wages [13] specifies one day off in seven and two recent studies of domestic work in different Indian states specify findings of four days off per month [14] and a maximum of one day off per week [15]. We also examined how much annual leave respondents were given. Only 4355 respondents received annual leave, and there was not a follow-up question about how much leave. As we could identify no study with data on the average number of days of annual leave for domestic workers in India, aside from reports of workers receiving no leave at all, we presumed this subset of respondents took 10 days annually, as this is the maximum entitlement for "casual leave" within India's Industrial Employment (Standing Orders)

Central Rules, 1946. This may over-estimate their annual leave, i.e., their hourly salary rate may in fact be even lower than we have estimated.

Respondents indicated in the survey how many hours they worked per day, so after these adjustments for days off per week and annual leave, we estimated mean hourly salary rates across all respondents and by state (Table 7). We compared this to state minimum wage levels as published by each state government's Labour and Employment Department in notifications under the Schedule of Employment for the years of the survey between 2015 and 2019: either minimum wages by hour specifically for domestic workers where listed or, where domestic work was not specified as a category, by selecting the rates for the category of Unskilled (as opposed to Semi-Skilled, Skilled, or Highly Skilled). As shown in Table 6, the proportion of all workers paid below the minimum wage is very high, 89%, and this proportion is as high as 99% in one state (Mizoram).

Table 7. Minimum wage calculations. Mean hourly salary, minimum wage requirements, and proportion of workers below the minimum wage by state.

	Number of Respondents	Mean Hourly Salary	Min	Max	Min Wage	Number of Workers under Min Wage	% Workers under Min Wage
All states	10,929	17.99423	0	1171		9746	89.17559
Assam	6984	15.79195	0	1171	30	6417	91.88144
Manipur	752	21.03252	0	79.4	28.1	613	81.51596
Meghalaya	1982	25.89278	1	576.9	40.5	1657	83.60242
Mizoram	360	11.39115	0	55.6	47.5	358	99.44444
Nagaland	254	11.75436	0	82	22	218	85.82677
Tripura	597	20.34429	0.7	98.4	29.2	483	80.90452

Two other important variables to consider in this dataset for understanding potential exploitation in the form of child labour are (i) the age of the respondents at the time of the survey and (ii) the age of the respondents when they started work. There was a statistically significant difference in the mean age of respondents and the mean age of respondents when starting work across the six states (one-way ANOVA: $p < 0.001$). Manipur had the highest mean age (38.6) and mean age when starting work (29.2), while Mizoram had the lowest mean age (21.7) and Nagaland the lowest mean age when starting work (Table 8). The mean age of the respondents varied from 36 to 39 for all states except Mizoram and Nagaland, where the average age of respondents was 22, and the mean age when individuals started work is lower in both Mizoram and Nagaland. Nagaland has a high SD (indicating that there is a substantial range).

Table 8. Deviation in age. The mean and standard deviation (SD) of the age of respondents at the time of the survey.

	Age of Respondent at Time of Survey		Age of Respondent When Starting Work	
State	**Mean**	**SD**	**Mean**	**SD**
Assam	37.6	11.3	28.1	10.2
Manipur	38.6	11.3	29.2	10.4
Meghalaya	36.3	10.8	22.4	9.1
Mizoram	21.7	6.0	19.4	4.7
Nagaland	22.0	9.7	18.1	9.1
Tripura	38.5	11.3	28.5	9.8

Of all the states included in the survey's non-random sample, Nagaland had by far the most respondents under the age of 14 ($n = 80$, 87.9%). A further ten children were located in Assam and one in Mizoram (Figure 11a). Assam had the majority of respondents who began work below the age of 14 (n = 385), followed by Meghalaya (n = 254), Nagaland (n = 139), Tripura (n = 190), Manipur (n = 14), and Mizoram (n = 5).

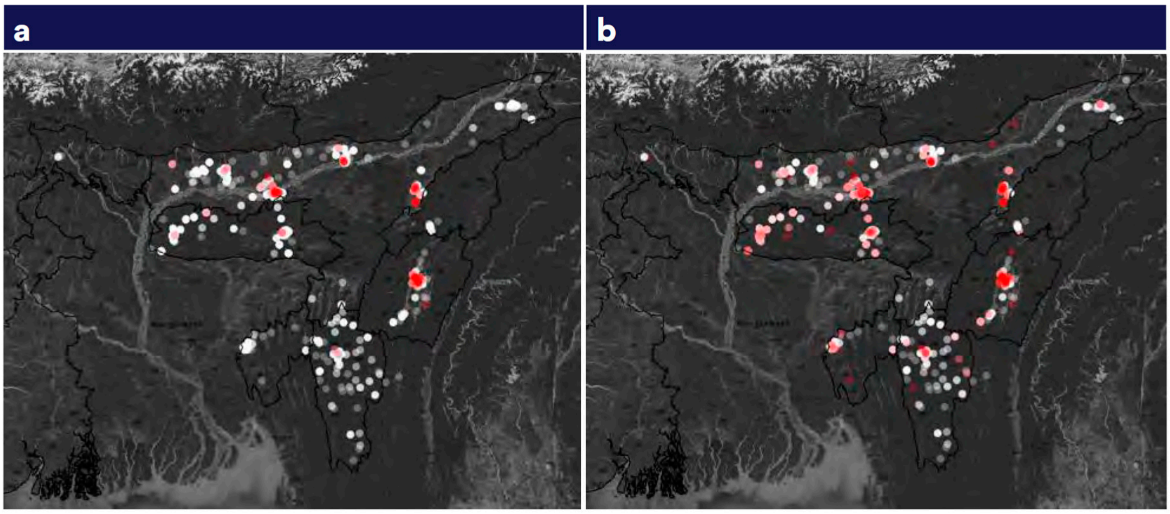

Figure 11. Locations of child labour. The maps show the (**a**) age of respondents and (**b**) the age of respondents when they started work. Any respondents at 14 years of age or older are depicted in white, while those below 14 years of age are depicted in red. State boundaries are outlined in black.

4. Discussion

The results contain new findings on minimum wage non-compliance, forced labour, and child labour. The findings cannot be generalized to the national level, as the CDI empowerment programme was designed for six states in Northeast India—a region with unique socio-economic features. However, in terms of the geospatial patterns we identified across the six states themselves, particular concentrations are not simply a function of where the CDI staff members were based. The interviewers travelled widely to achieve geographical coverage, enhancing our ability to discuss state-level patterns.

As well as enabling an identification of indicators for exploitative, forced, and child labour, the Domestic Workers Dataset demonstrates a current context of increasing scale and innovation in the modern slavery measurement approach. Specifically, it gives shape to three potential, emerging directions for measurement innovation: "found" data and participatory and citizen science methods.

4.1. Non-Compliance with Minimum Wage Rates

In response to the findings on non-compliance with minimum wage levels (Table 7), we examined state policies. By the time the surveys were being undertaken, 19 of the 31 states and Union territories in India had included domestic workers in the list of scheduled employments as against the Minimum Wages Act 1948: Andhra Pradesh, Assam, Bihar, Dadra and Nagar Haveli, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerela, Manipur, Meghalaya, Mizoram, Odisha, Puducherry, Punjab, Rajasthan, Tamil Nadu, Telangana, and Tripura. Only Nagaland, of the six states included in the Domestic Workers Dataset, was not on this list. In addition, as of 2019, Mizoram still had not fixed the wage rate for domestic workers [16], meaning that domestic work was included in the list of occupations that fall under the state's minimum wage requirements but without yet a minimum wage specified. This means that at the time of the surveying effort, employers in four of the six states were non-compliant with state minimum wage rates as specified for domestic workers for 81–92% of workers surveyed.

It is significant that Mizoram and Nagaland are the two states of the six surveyed that, at the time of surveying, had either not included domestic workers in the list of occupations that fall under state minimum wage requirements (Nagaland) or had not yet specified the wage (Mizoram). These are the states with the lowest hourly salary and the largest proportion of workers paid below the minimum wage (Table 7). The lack of a minimum wage rate for domestic workers may explain these findings and therefore confirm the importance of state minimum wage requirements to domestic workers (albeit still not removing the problem of minimum wage non-compliance, as evidenced in the results for the other four states). Mizoram also had a significantly higher average number of hours worked, as well as lower salary rates per hour, which may indicate a higher risk of exploitation.

4.2. Indicators of Forced and Child Labour

Alongside the signals of a lack of decent work from this minimum wage analysis (Table 7), our examinations of the dataset revealed key indicators for forced labour. Most respondents had no work contract, access to medical care, social security in place, or days off (forced labour indicator = abusive working and living conditions [10]). A total of 85% of the domestic workers were from marginalised social groups, including Scheduled Castes/Dalits, and most had left school by the age of 14 (forced labour indicator = abuse of vulnerability; [10]). In addition, nearly 34% of the respondents were live-in domestic workers, for whom exploitation threat tends to be higher. Although types of work did not vary significantly between states, statistically significant differences indicate some states are potentially higher risk for poor working conditions than others—which may help to target empowerments and worker rights programmes for particular states.

The data also confirm the presence of child labour. The Child and Adolescent Labour (Prohibition and Regulation) Act of 1986 in India defines any person under the age of 14 as a child, and the employment of children as illegal. There are respondents included who were under the age of 14, as well as respondents who started working before the age of 14. This is indicative of illegal practices in domestic work in the region surveyed.

The data suggest significant child labour rates. Although a small percentage of the sample were children under 14 (n = 91, 0.8%) at the time of the survey, this is because the surveys were only targeted at adults. The target respondents were domestic workers in the process of signing up to the CDI "Domestic Workers Union Structure" project, which aimed to empower adult domestic workers via union-like structures. Over 99% of the individuals who chose to participate in the programme and register with the FDWA (and were therefore surveyed) were aged 14 or older. Nonetheless, 6% (816 respondents) had begun work before the age of 14. This is significant for six states that are not normally considered to have high incidences of child labour. Five other states (Uttar Pradesh, Bihar, Rajasthan, Maharashtra, and Madhya Pradesh) are understood to constitute the majority of total working children in India [17]. Even the figure of 6% may therefore suggest that official figures in the national census for child domestic workers in India (0.52 million) are too low.

We analysed the geographical distribution of this child labour. As the data seem to show that Nagaland and Mizoram have a lower average age for domestic workers and also lower salary rates, it may be valuable to focus on these two states for targeted programming on child labour risks that addresses specific indicators for vulnerability—as well as Assam and Meghalaya, states where higher numbers of workers began work below the age of 14.

4.3. Significance within Efforts to Measure Domestic Work

These findings on minimum wage non-compliance and indicators of forced and child labour have additional significance because, to our knowledge, the new Domestic Workers Dataset is the largest single set of surveys with domestic workers to date. For example, at a multi-country level, the ILO has compiled data from national labour force surveys that include domestic worker-reported hours of employment [2], and Anti-Slavery International has surveyed 1465 child domestic workers in six countries [18]. At local or regional levels, there have been multiple smaller-scale, bespoke domestic work surveys. Oxfam surveyed 114 domestic workers in Nairobi, Kenya [19]; Gurtoo surveyed 487 domestic workers across two cities in Karnataka, India [20]; and Tariq et al. surveyed 406 domestic workers in Karachi, Pakistan [21].

At a national level, efforts to survey domestic workers include a baseline study to establish the prevalence of child domestic work in Ghana that surveyed 2480 households [22] and a national survey of domestic workers in the United States that interviewed 2086 domestic workers from 71 countries [23]. In India specifically, a survey of several thousand domestic workers conducted for the Catholic Bishops Conference of India (published as the *National Socio-Economic Survey of Domestic Workers* in 1980) covered 12 cities and determined that 17% of the domestic workers interviewed were under the age of 15 [24]. It laid out a manifesto for improving conditions for domestic workers in India. In 2021, the Indian government announced it would complete a survey of 150,000 domestic workers to estimate the number across the country and collect data on characteristics and conditions (results are not yet released, see [25]).

Relative to other studies of domestic work—multi-country, national, regional, and local—this dataset of nearly 12,000 surveys is very significant in its geographical scope combined with its fine scale. The dataset provides unprecedented access to information about a hidden workforce.

4.4. Significance within Efforts to Measure Exploitation in India

Beyond a domestic work focus, the dataset is also significant in its scale relative to other studies of labour exploitation and forced labour in India more broadly. India has the highest estimated number of people in modern slavery in the world, according to the 2023 Global Slavery Index (GSI) by Walk Free: 11 million of an estimated 49.6 million people enslaved globally (and an estimated prevalence of 0.8% of India's population). It also has the highest rate of change of all countries in GSI estimations across the 10 years of the index, in terms of estimated total numbers in modern slavery: an average change of 4,456,348 people across the five editions of the GSI to date (2013, 2014, 2016, 2018, 2023).

Alongside these swings in total numbers, the GSI has extensive data gaps for India within each edition. The 2013 GSI did not use survey data, and the 2014 GSI included data from nationally representative, random-sample surveys in only seven countries and not India. The 2016 GSI used a survey in India covering 15 states and all sectors and forms of exploitation but with a total sample of only 14,000. The 2018 GSI figure for India was based on the same 2016 survey. The GSI team explained that the shift in estimated numbers of people in modern slavery in India from the 2016 GSI to the 2018 GSI (−10 million in 2018) was due to changes in the GSI prevalence estimation methodology rather than updated surveying [26]. Finally, in the 2023 GSI, the index methodology material explained that "coverage is limited or lacking" and the "sample of countries also omits some of the most populous countries", including India. It added that "while surveys were conducted in India and Pakistan, fragility of the underlying data led to their exclusion", and suggested that conducting surveys during the COVID-19 pandemic is "likely to have had an impact on data quality" [27](202). It is not clear whether the figures for India in the 2023 GSI were still based on the surveys conducted in 2016 or were generated through the GSI's imputation model. These data gaps and extreme shifts in numbers suggest high levels of difficulty with measurement in India, specifically.

Beyond the GSI, attempts to estimate any form of modern slavery, forced labour, and human trafficking (including domestic servitude and bonded labour) in India have been limited. A survey conducted in 10 states (1000 villages) in 1978 by the Gandhi Peace Foundation and the National Labour Institute remains the most geographically extensive survey on bonded labour in India published to date [28]. It estimated the total number of agricultural bonded labourers at 2.62 million. However, in 1996, 16 states in India were directed by the Supreme Court to collect information on the prevalence of bonded labour, and the resulting surveys yielded a total estimate across all 16 states of only 29,016 bonded labourers—an estimate lower than even the numbers of people formally recorded as exiting bonded labour (which was an average of 40,768 per year across those 16 states in the seven years subsequent to the 1996 surveys) [29].

The 21st century has not brought more clarity. Aside from the GSI's national-level estimates that have included India (2013–2023), a 2005 ILO report on bonded labour incidence in India summarised evidence on causes and patterns but did not offer prevalence estimates or new survey data [29]. The US State Department's annual Trafficking in Persons Report rarely reports prevalence estimates, but in 2013 it reported estimates of between 20 million and 65 million people in forced labour in India (mostly bonded labour) [30], and in 2020 it reported NGO estimates of at least 8 million trafficking victims in India [31]. The most rigorous bonded labour estimate in India to date is a district-level study rather than a national one: Parks et al. surveyed 4306 labourers in three districts in Karnataka to estimate 558,334 bonded labourers working in these districts at the time of the survey [32].

4.5. Context of Modern Slavery Estimation Approaches

This significant scale of the Domestic Workers Dataset, within studies of both domestic work globally and exploitation more broadly (across all sectors) with India, has the wider context of current efforts to measure the extent of modern slavery (including forced labour and forced marriage) at international, national, regional, and local levels, using a range of techniques at the micro- and macrolevels [33]. The work of the CDI itself, including its surveying and registration of domestic workers, is part of this anti-slavery landscape: its work is supported by the Arise Foundation, which focuses on supporting front-line groups to develop interventions against modern slavery and to measure the scale of their impact through new research.

Understanding the true nature and extent of exploitation in any given local or national context is fraught with methodological difficulties, stemming from the fundamental problem that victims of human trafficking, forced labour, and modern slavery are a hard-to-find population. But recent innovations have delivered the most reliable estimates of modern slavery's scale to date: Multiple Systems Estimation (MSE) [34,35], multi-level modelling based on random sample survey instruments [4], the network scale-up method (NSUM) [36], and hyperlocal street surveys combined with non-standard data into insight tiles [37].

For example, Bales et al. [34] used MSE to estimate that the total number of people in modern slavery in the UK was between 10,000 and 13,000. The MSE approach uses multiple samples and a 19th-century statistical technique called "capture–recapture". The UK analysis was based on six different lists of people reported as experiencing modern slavery, including the UK government's own National Referral Mechanism. The researchers fit a series of models across the different lists to make the best estimate possible, given the sparse coverage of data across sources. Then, in 2019, Bales et al. carried out the same kind of estimation for the US city of New Orleans [35]. This was one of the first attempts to quantify modern slavery or human trafficking at the city level and found that the estimated total number of enslaved people was between 650 and 1600. Key was the use of de-identified data provided by local organisations: law enforcement, social service providers, housing providers, and legal assistance providers. The research team recommended that local agencies should receive training on data collection and employ analysts so as to analyse their data, report findings, and use the data to improve victim services.

MSE is only possible in country contexts where multiple administrative lists of victims are maintained. Far more common for modern slavery measurement is the survey-based approach taken by the CDI for the Domestic Workers Dataset. For example, the 2022 Global Estimates of Modern Slavery (from which 2023 GSI drew its national-level figures) report that 49.6 million people were in modern slavery on any given day in 2021 [4]. Behind this estimate are surveys administered by Gallup that collect data on individual vulnerability to modern slavery in high-prevalence countries. Other survey-based studies of slavery/trafficking prevalence include the trafficking of migrant workers in San Diego [38]; the forced marriage of Myanmar women in China [39]; the trafficking of minors in the adult entertainment sector in Kathmandu, Nepal [40]; and the trafficking of Internally Displaced Persons in Kenya [33,41].

To better enable surveying in contexts where it is impossible to access victims directly and where stigma is a major factor for respondents, a research team introduced the NSUM as an innovation in modern slavery measurement. This innovation combined 3600 household surveys and the NSUM to produce national prevalence estimates of the number of children who were victims of trafficking for child sexual exploitation material (CSEM) production in the Philippines: one in every hundred children in the Philippines [36]. The surveys asked respondents how many adult traffickers and child victims they knew that were involved in the trafficking of children to produce CSEM.

To achieve fine-grained results at the hyperlocal level, another research team introduced the innovation of combining street-level data with non-standard data streams to generate a forced labour heat map for the city of Dar es Salaam, Tanzania [37]. Dar es Salaam has a population of over 6 million across 90 administrative wards. But the research team believed there were too many people in each ward for the model to be informative. They used a community-generated map produced in collaboration with the dLab, a local NGO that promotes data literacy. This map sees the city as over 400 hyperlocal sub-wards, divided by decision-making structures called "shinas". Each shina is administered by a "mjumbe", a community-appointed and trusted point of contact for local households on issues of public services and resource allocation. These individuals represent anywhere from 30 to 200 households to the government.

Working with these vernacular geographies, the team trained local volunteers to survey people in each sub-ward about its features. The process involved 30 team leaders and 163 local participants with hand-held devices who surveyed more than 5000 respondents across the 443 sub-wards of Dar es Salaam. The survey sought information on 30 known indicators of child labour, forced labour, and forced marriage and included the following question: "I know there are some people in this sub-ward being forced to work against their will" (answers could range from "strongly agree" to "strongly disagree"). By combining the survey data with layers of non-standard data that act as proxies for vulnerability to slavery (including telecommunications and transport data), the team built a predictive model that could then visualise any of the city's blocks through what they term "insight tiles". They moved beyond national-level estimates to understand what predicts the presence of slavery locally.

The Domestic Workers Dataset has the context of these new efforts to introduce data-gathering innovations for understanding the nature and scale of slavery, forced labour, and exploitation. The dataset combines the large-scale surveying approach of the Global Estimates with the locally embedded approach of Lavelle-Hill et al. (163 local volunteers conducting surveys in Dar es Salaam) and the emphasis on front-line data of Bales et al. (eight datasets from front-line service providers in New Orleans). The Domestic Workers Dataset was not intended as a study of exploitation prevalence: the 11,759 individual surveys represent a convenience sample. But the scale and detail of the dataset suggest that by adjusting its survey design, the CDI and its network of Sisters could generate data towards new prevalence estimates for exploited, forced, and child labour in domestic work. A revised survey with a clear sampling frame that specifies the population of interest, takes a random sample, and seeks balance in sample numbers between states (so as to minimize the variation in the number of respondents) would allow generalisations to be made.

The unique access of the CDI to domestic workers via its front-line network of Sisters also suggests it could adjust the surveys to successfully elicit key vulnerability factors that *explain* the prevalence of exploitation. Additional questions could include details about the proximity of the individuals' family homes to a school (to understand if distance from school correlates to lack of education) and about the individuals' proximity to and awareness of community support groups (to understand their current sense of isolation versus connection to a wider community of domestic workers). Survey questions could aim to capture workers' experiences, perceptions, and understandings of conditions, as well as core demographic and geographic information, in order to significantly expand and enrich the available data on labour exploitation.

4.6. Significance for "Found" Data Approaches

This fact that the Domestic Workers Dataset did not originate within a research study—was not intended as a study of exploitation prevalence—illuminates one of several more specific modern slavery measurement approaches and potential future directions: "found data" [42,43]. Sometimes termed organic data [44], naturally occurring data [45], or data in the wild [46], these are data not intended to support prevalence estimates, assessments of vulnerability/risk factors, or other statistical analysis but which nonetheless can be analysed for key research findings. The study in Tanzania [37] contained one example of "found" data, the layers of telecommunications and transport data used as proxies for vulnerability, and the New Orleans study contains another—victim lists held by service providers [35].

An example of "found" data at an even larger scale is the hotline call data with information on 164,839 victims of trafficking in the US (2007–2023), held by US-based anti-trafficking NGO Polaris. The largest known dataset on human trafficking in North America, this grew out of more than a decade of operating the US National Human Trafficking Hotline. Polaris makes this "found" data from hotline calls available for research and itself has analysed more than 32,000 cases of human trafficking from the dataset to develop a classification system for 25 types of human trafficking [47]. Similarly, the charity Unseen operates a national modern slavery helpline for the UK and maintains data on 29,762 potential victims of modern slavery indicated to the helpline, which could be analysed in similar ways.

As was the case with the data collected by the eight front-line organisations in New Orleans used for MSE [35], the "found" data of service providers like Polaris and Unseen can offer rich and nuanced information for analysis and interpretation—including through research that combines "found" and "designed" data. The largest-scale example to date of combining "found" and "designed" data for modern slavery measurement is within the Global Estimates, which integrates case data from the Counter-Trafficking Data Collaborative (CTDC). Led by the IOM, the CTDC combines data on over 100,000 cases of trafficked people from across the world, provided by front-line organisations on victims they have identified or assisted. The collection aims to provide capacity for cross-border, inter-agency data analysis and therefore improved evidence for policy and programming. It is also used within the Global Estimates in combination with survey datasets to estimate the forced commercial sexual exploitation of adults and commercial sexual exploitation of children. The Global Estimates' surveys only captured forced labour, not commercial sexual exploitation. The CTDC dataset comprises cases of trafficking for both sexual and forced labour exploitation and includes information on the profile of survivors. The Global Estimates research team therefore estimated the odds ratios of forced commercial sexual exploitation relative to forced labour exploitation using the CTDC database and applied these odds to the corresponding Global Estimates of forced labour exploitation of adults and children derived from the national surveys [27]. In this CTDC example, the front-line organisations did not generate data for the purpose of research into prevalence and vulnerability. Their case information is "found" data that the Global Estimates team then combined with "designed" data (surveys) for prevalence estimation.

However, the fastest-growing category of "found data" for modern slavery research is satellite data (e.g., [48], see also [49]) which researchers are using in combination with "ground-truth" surveys to reveal patterns of vulnerability and exploitation. For example, the Rights Lab's Slavery from Space programme uses satellite remote sensing data that are routinely collected to map the infrastructure associated with slavery and produce new estimates of forced labour sites and vulnerability factors. The programme has completed a mapping of brick kilns across the Brick Belt of South Asia, where a high proportion of labour is bonded (see [50–53]), and has also mapped sites of forced labour in cobalt-mining in the DRC [54,55], fish-processing in Bangladesh [56], agriculture in Greece [57], and deforestation in Mozambique [58], among other countries and sectors.

The Domestic Workers Dataset's scale and detail is another important demonstration of what "found" datasets can offer. Like the case data gathered by the contributors to the CTDC, the Domestic Worker Dataset represents data gathered by people offering front-line services—a context of seeking information towards further liberatory action or the provision of recovery services and prevention programming. As a data-gathering approach, the deployment of surveys as part of labour rights network registration could be expanded to other countries where similar networks of Sisters exist. In multiple countries where large networks of Sisters are embedded in vulnerable communities, they may be able to gather further data as a byproduct of their existing anti-exploitation and rights awareness work—"found data" that when cleaned and analysed can reveal patterns of labour exploitation, child labour, and forced labour. In addition, by adjusting surveys to better capture features of exploitation, the CDI would be combining a "found" data approach with elements of "designed" data.

The surveys' geolocation data could also provide complementary evidence to data being collected through other means, including remote sensing. A combination of geospatial data on high-risk sites in India with the surveys' geolocation data would support the detection and comparison of patterns within and between states [51]. This may help to guide the network of Sisters towards working alongside exploited labourers in particular hotpots. In turn, the Sisters may be a unique network for potential "ground-truthing" of Slavery from Space data. Remote sensing for EO data can help to fill the data gap in developing countries, but the optimal use of the information carried in EO data requires ground data—the verification of what is identified from space and the initial rich description of what to look for in satellite imagery in the first place. The areas across which high-risk industries are spread can be vast—for example, the areal extent of the "Brick Belt" is 1,551,997 km^2. The network of Sisters could effectively ground-truth these EO data: it is a network of thousands of people with a ground-truthing capacity that goes beyond what even the largest in-country NGO could achieve. This would be an example of one form of "found" data (information gathered as workers are registered in labour rights programmes) being combined with another (satellite imagery) to form "designed" data that give a new, layered picture of exploitation hotspots.

4.7. Significance for Participatory Data Approaches

The origins of the Domestic Workers Dataset as "found" data gathered by front-line workers reveal a second specific modern slavery measurement approach and potential future direction: participatory data approaches, where data investigation is driven by local communities towards a better understanding of local issues. Taking a bottom–up, grassroots approach need not infer datasets that are small in size. Participatory data approaches can include medium or large datasets and work with quantitative, geographic, or qualitative data—numbers, maps, interviews, narratives, images, and surveys. Participatory data also do not imply a lack of rigour or complexity, rather a focus on matching data-gathering and analysis to the interests and needs of a community, making community members (for example the network of Sisters in India and the FDWA) the data-owners and data-users and empowering individuals and local actors with actionable insights.

In one example of a participatory data approach, the anti-trafficking NGO HAART in Kenya surveys survivors of trafficking and at-risk communities in order to then feed those insights back into grassroots awareness toolkits and training manuals. Its participatory approach means it works closely with survivors, considers what survivors would find useful in terms of data, and tries to understand how community actors themselves can better examine data to tackle human trafficking locally and regionally.

In another example, the mobile app Apprise, deployed in Thailand in the fishing, seafood-processing, and sexual exploitation sectors, supports communication between front-line responders and vulnerable workers. Workers control their own data collection:

they select their preferred language for the interview while answering the questions in privacy and anonymity and can ask for help to leave their current situation. The app then reports any indications of vulnerability to the front-line responder. Its creators report that it has improved the identification of victims of human trafficking and forced labour, highlighted the full range of migrant workers' experiences, and provided microdata that can inform migration policy [59].

Other anti-slavery groups have built participatory approaches into the work of updating data collection approaches. For its 2019 *Measurement*, *Action*, *Freedom* report, which evaluated the performance of all governments on tackling modern slavery, Walk Free ran workshops with survivors of slavery to assess the indicators of the government response framework (for example, specific mechanisms in the areas of criminal justice, supply chains, and victim support). One workshop was in the UK, hosted at the Rights Lab with the Survivor Alliance, a global network of slavery and trafficking survivors. Another was in India, hosted with the survivor leader collective Uttham and the Survivor Alliance. Each two- or three-day workshop with survivors reviewed Walk Free's conceptualisation of a government response and asked survivor leaders what was missing from its current framework. Walk Free incorporated the findings from these workshops into the conceptual framework in order to gather data against the new indicators [60].

A front-line, "found" dataset, the Domestic Worker Dataset, has the potential to be a pioneering example of participatory data as well. Embedded in the communities where they surveyed, providing front-line health, economic, and educational services to domestic workers, the network of Sisters may have a trusted status that goes beyond that of the other front-line service providers (for example, the helpline operators at Polaris and the law enforcement teams in New Orleans). Their community presence may provide the potential for rich, participatory data with insights beyond those that community outsiders can gain.

To extend the participatory approach, the survey findings and on-going design and delivery processes could now be handed back to domestic workers via the FSWA and its 600+ local groups. The CDI could engage domestic workers themselves in responding to the dataset and designing a new survey instrument, reflect on current findings from the perspective of workers, and discuss what questions a new iteration of the survey should include. Domestic workers themselves may suggest new categories and phrasing that can uncover vital insights. By then running the same analysis on the second dataset, drawn from a new round of co-designed surveys, we would be able to identify any differences between the two datasets and learn from this new, major example of a grassroots, participatory data–impact cycle. Part natural experiment and part randomized controlled trial, a comparison of one dataset created without direct participant input and a second created *with* that input has the potential to make the strongest case to date for the importance of participatory, grassroots data work in the area of modern slavery and labour exploitation.

4.8. Significance for Citizen Science Approaches

Participatory data approaches can also include data sourced via the crowd, leveraging citizen-generated data. This is a third specific modern slavery measurement approach and potential future direction that the Domestic Workers Dataset helps to reveal. The use of citizen scientists—usually non-expert volunteers—to gather and interpret data has dramatically increased in the past five years. The proliferation of citizen science and crowdsourcing platforms make it relatively easier to organise projects, but citizen interests are highly dynamic. Initiatives that are highly topical can generate high volumes of data but risk quickly losing public interest. The "non-expert" nature of participants can also risk data quality and accuracy. Data collected via citizen science approaches can be "noisy" because of the redundancies and gaps arising from human behaviour, and it can be difficult to establish a formalised process to robustly operationalise ad hoc voluntary inputs.

The field of modern slavery and labour exploitation has utilised citizen science on just a handful of occasions so far. For example, the Safe Car Wash app allows drivers to respond to a check list of key factors that may suggest modern slavery or labour exploitation in hand car washes. It was downloaded 8225 times in its first year after launch by the Church of England and the Catholic Church in England and Wales, and drivers made more than 900 reports of potential cases over a five-month period [61]. In another example, a project focused on brick kilns led by Boyd et al. [50] included a citizen science element. The research asked volunteers to help identify brick kilns—known sites of bonded labour—in satellite imagery of the Brick Belt across India, Bangladesh, Nepal, and Pakistan. The final result was the first rigorous estimate of the number of brick kilns across the Brick Belt—sites that have a high prevalence of forced labour. In a follow-up study analysing the value of citizen science, Boyd et al. found that citizen scientists can be exceptionally good at producing data quickly and that "fulfilment" was a key motivator for volunteers: that "motivated and engaged citizens" for this Slavery from Space work led to "better data quality, levels of involvement and larger data sets" [52].

Not only a major example of found, front-line data, and potentially an example of participatory data, the Domestic Workers Dataset is also an example of citizen science—a network of local, embedded, and volunteer researchers, not data professionals, who gathered data on a scale and over a time period that would not have been achievable by visiting researchers or international surveying companies and in contexts (the vulnerability and invisibility of domestic workers in private households) that would not have been accessible by outsiders. Though not explicitly designed as such, the CDI surveying initiative may represent a new form of the now 25-year-old practice of citizen science. Uniquely well positioned as a network of active, embedded volunteers who work discreetly alongside people in some of the most high-risk and vulnerable areas of the world, the Sisters can be understood as citizen scientists. Going forward, these citizen scientists could work alongside EO and other data scientists to identify sites and signals of slavery in novel data streams, in India and other countries.

5. Conclusions

The availability and quality of data on modern slavery and human trafficking, as well as on many related sustainable development issues and targets, remains an issue. Ahead of the launch of the Sustainable Development Goals (SDGs) in 2015, the UN observed that "too many countries still have poor data, data arrives too late and too many issues are still barely covered by existing data" and called for a "data revolution" for sustainable development [62]. However, in spite of intergovernmental and government efforts to gather data in support of monitoring SDG progress, in 2023, the UN observed that "persistent data gaps still challenge our SDG data landscape" and pointed to multiple SDGs where "less than half of the 193 countries or areas have internationally comparable data since 2015" [63].

As both a community of interest and a community of *intent* with regard to data collection, the Sisters' surveying approach has the potential to greatly develop the global knowledge base on labour exploitation and modern slavery, including for monitoring progress towards achieving SDG 8.7 ("take immediate and effective measures to eradicate forced labour, end modern slavery and human trafficking and secure the prohibition and elimination of the worst forms of child labour"). The Domestic Workers Dataset offers a unique opportunity to understand people at high risk of trafficking and labour exploitation whose work was previously unobservable. It also indicates and helps give shape to three potential ways forward within modern slavery measurement innovation: "found" data, participatory approaches, and citizen science.

In turn, the dataset's illumination of these emerging areas of innovation suggests there are new opportunities for future capacity-building on human rights data-gathering for networks of Sisters—towards more robust measurement of the scale of exploitation. These opportunities include new survey methods and approaches, in more countries, and the potential to extend their techniques into citizen science "ground-truthing" of EO data. As we enter the final phase of the 2015–2030 agenda for sustainable development, "found", participatory, and citizen science data gathered by networked front-line organisations may be a route towards a fuller understanding of the scale, nature, causes, and consequences of modern slavery, human trafficking, and labour exploitation.

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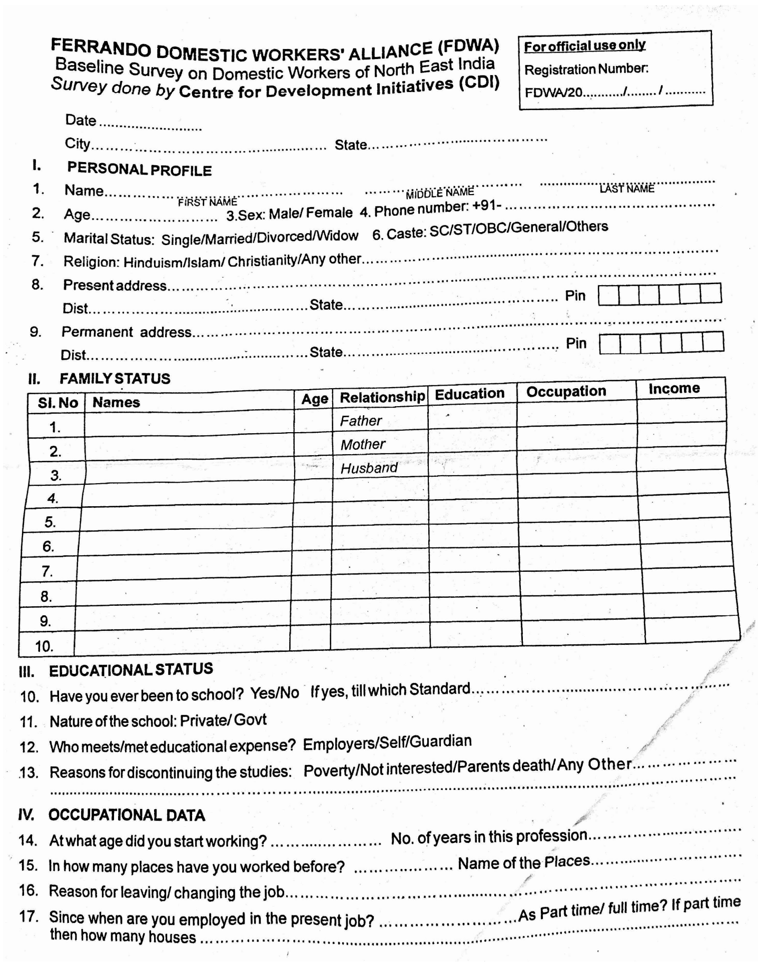
Appendix A. Blank Copy of Domestic Worker Survey



FERRANDO DOMESTIC WORKERS' ALLIANCE (FDWA)
Baseline Survey on Domestic Workers of North East India
Survey done by **Centre for Development Initiatives (CDI)**

For official use only
Registration Number:
FDWA/20........../......../..........

Date ....
City.. State.......................................

I. PERSONAL PROFILE

1. Name.................................. ....
FIRST NAME MIDDLE NAME LAST NAME
2. Age........................ 3.Sex: Male/ Female 4. Phone number: +91-.......................................
5. Marital Status: Single/Married/Divorced/Widow 6. Caste: SC/ST/OBC/General/Others
7. Religion: Hinduism/Islam/ Christianity/Any other...
8. Present address...
Dist.......................................State....................................... Pin
9. Permanent address...
Dist.......................................State....................................... Pin

II. FAMILY STATUS

Sl. No	Names	Age	Relationship	Education	Occupation	Income
1.			*Father*			
2.			*Mother*			
3.			*Husband*			
4.						
5.						
6.						
7.						
8.						
9.						
10.						

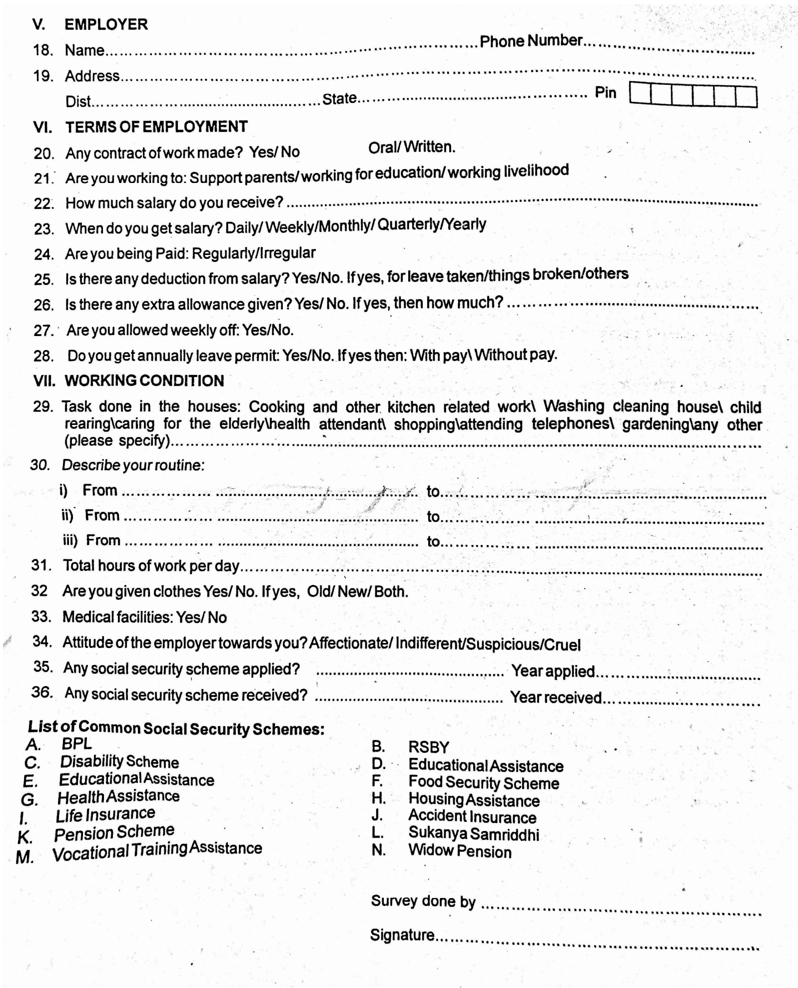
III. EDUCATIONAL STATUS

10. Have you ever been to school? Yes/No If yes, till which Standard.......................................
11. Nature of the school: Private/ Govt
12. Who meets/met educational expense? Employers/Self/Guardian
13. Reasons for discontinuing the studies: Poverty/Not interested/Parents death/ Any Other.......................
....

IV. OCCUPATIONAL DATA

14. At what age did you start working? .... No. of years in this profession.............................
15. In how many places have you worked before? .... Name of the Places.............................
16. Reason for leaving/ changing the job...
17. Since when are you employed in the present job? ....As Part time/ full time? If part time then how many houses ....

Figure A1. *Cont.*



V. EMPLOYER

18. Name..Phone Number..................................
19. Address..

Dist....................................State.. Pin

VI. TERMS OF EMPLOYMENT

20. Any contract of work made? Yes/ No Oral/ Written.
21. Are you working to: Support parents/ working for education/ working livelihood
22. How much salary do you receive? ....
23. When do you get salary? Daily/ Weekly/Monthly/ Quarterly/Yearly
24. Are you being Paid: Regularly/Irregular
25. Is there any deduction from salary? Yes/No. If yes, for leave taken/things broken/others
26. Is there any extra allowance given? Yes/ No. If yes, then how much? ....
27. Are you allowed weekly off: Yes/No.
28. Do you get annually leave permit: Yes/No. If yes then: With pay\ Without pay.

VII. WORKING CONDITION

29. Task done in the houses: Cooking and other kitchen related work\ Washing cleaning house\ child rearing\caring for the elderly\health attendant\ shopping\attending telephones\ gardening\any other (please specify)..
30. *Describe your routine:*
    i) From .... to..............................
    ii) From .... to..............................
    iii) From .... to..............................
31. Total hours of work per day..
32. Are you given clothes Yes/ No. If yes, Old/ New/ Both.
33. Medical facilities: Yes/ No
34. Attitude of the employer towards you? Affectionate/ Indifferent/Suspicious/Cruel
35. Any social security scheme applied? .... Year applied..............................
36. Any social security scheme received? .... Year received..............................

List of Common Social Security Schemes:

A. BPL
B. RSBY
C. Disability Scheme
D. Educational Assistance
E. Educational Assistance
F. Food Security Scheme
G. Health Assistance
H. Housing Assistance
I. Life Insurance
J. Accident Insurance
K. Pension Scheme
L. Sukanya Samriddhi
M. Vocational Training Assistance
N. Widow Pension

Survey done by ....

Signature..............................

Figure A1. Blank copy of domestic workers survey. The surveys were completed by hand between 2015 and 2019.

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