International Labour Organization

unicef
for every child

METHODOLOGY OF THE 2024 ILO-UNICEF GLOBAL ESTIMATES OF CHILD LABOUR

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ACRONYMS AND ABBREVIATIONS

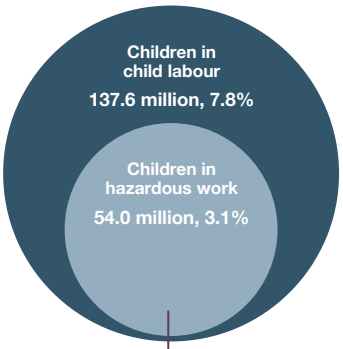
GDP	Gross domestic product
ICLS	International Conference of Labour Statisticians
ILO	International Labour Organization
ISCO	International Standard Classification of Occupations
LASSO	Least Absolute Shrinkage and Selection Operator
MICS	Multiple Indicator Cluster Survey(s)
PPP	Purchasing power parity
SDG	Sustainable Development Goal
SNA	System of National Accounts
UNICEF	United Nations Children's Fund
UN-WPP	United Nations World Population Prospects
USAID	United States Agency for International Development

EXECUTIVE SUMMARY OF KEY STATISTICS

Current situation

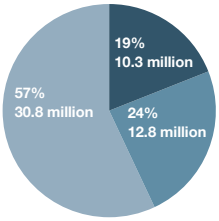
Child labour still affects nearly 138 million children worldwide; 54 million of these children are in hazardous work

Number and percentage of children aged 5 to 17 years in child labour and hazardous work



Hazardous work occurs among children of all ages

Number and percentage distribution of children aged 5 to 17 years in hazardous work, by age

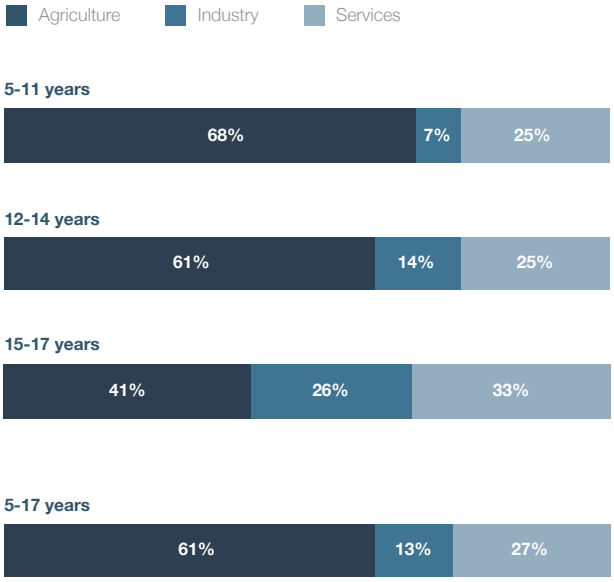


- 5-11 years
- 12-14 years
- 15-17 years

Notes: For statistical measurement, hazardous work includes work in designated hazardous industries and/or hazardous occupations and/or work performed for 43 or more hours per week. Due to rounding, the number of children in hazardous work by age does not add up to the global total.

Most child labour is in agriculture, although the relative share diminishes as children grow older

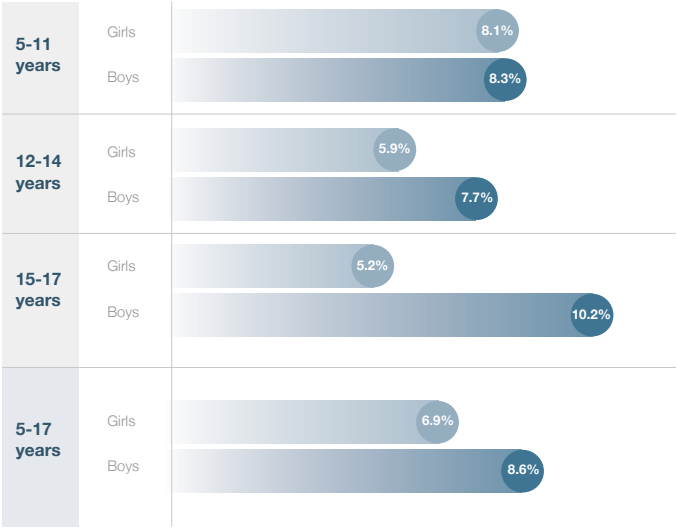
Percentage distribution of children aged 5 to 17 years in child labour, by age and branch of economic activity



Note: Due to rounding, some totals do not add up to 100 per cent.

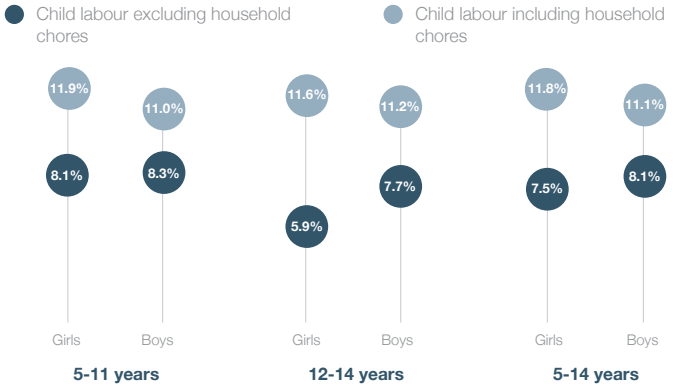
With age, child labour becomes progressively more common among boys than girls

Percentage of children aged 5 to 17 years in child labour, by age and sex



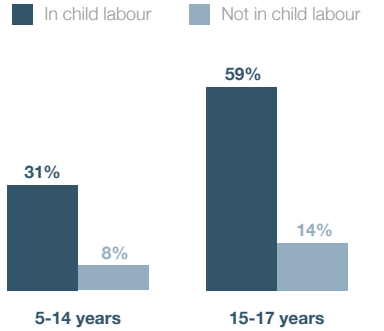
Factoring in household chores results in a slightly larger share of girls than boys in child labour

Percentage of children aged 5 to 14 years in child labour (including and excluding household chores performed for 21 or more hours per week), by age and sex



Child labour dramatically increases the likelihood that a child will be denied the chance to go to school

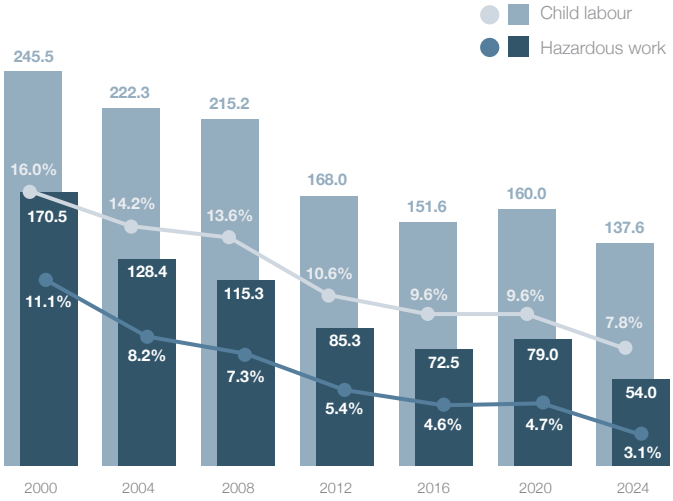
Percentage of children aged 5 to 17 years not attending school, by age and child labour status



Trends and projections

Over the last four years, the world has returned to a path of progress to end child labour

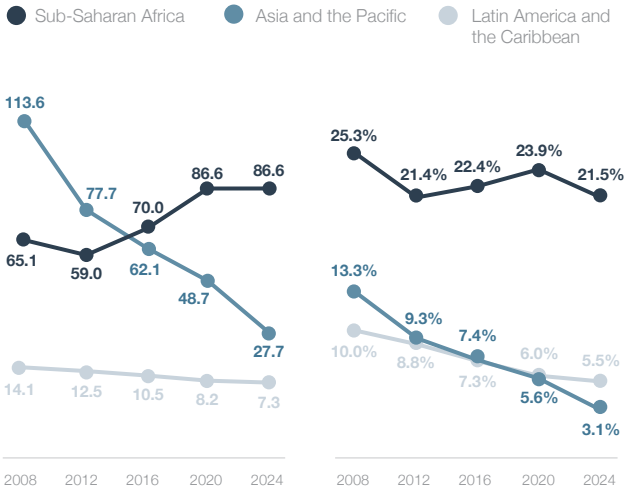
Number (in millions) and percentage of children aged 5 to 17 years in child labour and hazardous work



Note: For statistical measurement, hazardous work includes work in designated hazardous industries and/or hazardous occupations and/or work performed for 43 or more hours per week.

All regions have seen some progress against child labour since 2020

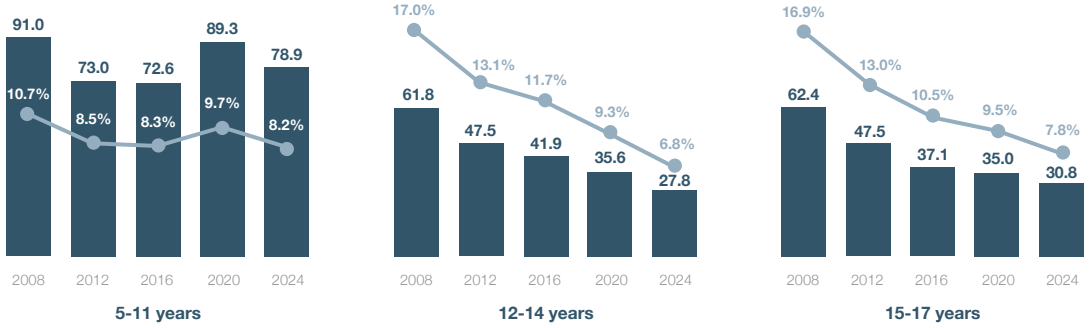
Number (in millions) and percentage of children aged 5 to 17 years in child labour, by ILO region



Notes: These figures show regional groupings used for ILO reporting. Comparable historical data prior to 2016 were not available for other regions.

Progress against child labour has been slower and more uneven among younger children

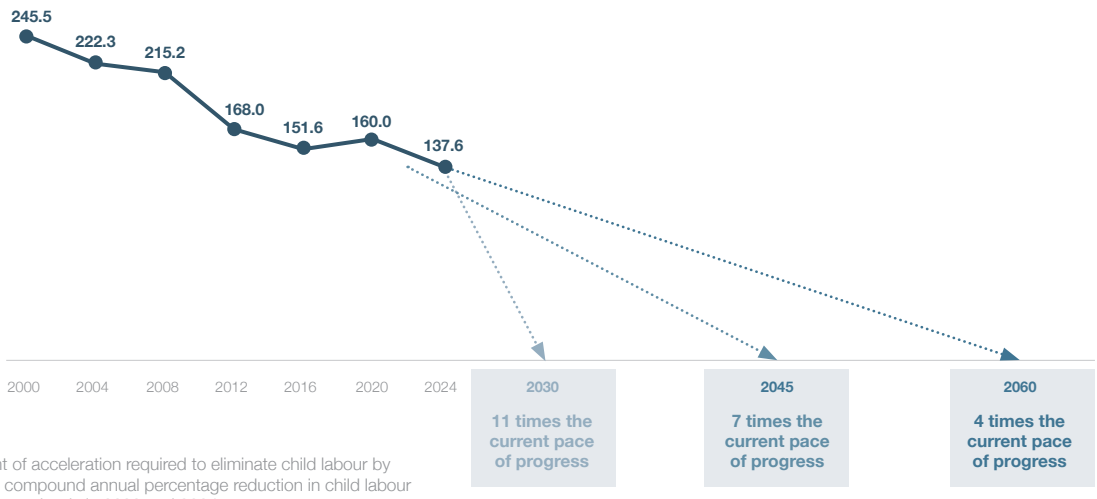
Number (in millions) and percentage of children aged 5 to 17 years in child labour, by age



Note: Due to rounding, the number of children in child labour by age in 2024 does not add up to the global total.

Despite recent gains, the fight against child labour will continue for decades into the future without rapidly accelerating progress

Number (in millions) of children aged 5 to 17 years in child labour and amount of acceleration required to eliminate child labour by different years



Note: These scenarios depict the amount of acceleration required to eliminate child labour by different years in the future based on the compound annual percentage reduction in child labour implied by the difference between prevalence levels in 2020 and 2024.

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1. INTRODUCTION

Since 1995, the International Labour Organization (ILO) has released seven consecutive editions of the Global Estimates of Child Labour. The first edition estimated that 250 million children worldwide were in child labour. In the current seventh edition, this figure has declined to 138 million children, reflecting the significant efforts made to combat child labour over the past three decades. The Global Estimates aim to draw attention to the continued persistence of child labour on a global scale and reveal areas where various stakeholders should focus their efforts in the ongoing collaboration to eliminate child labour.

The 2024 Global Estimates of Child Labour were jointly produced by the ILO and the United Nations Children's Fund (UNICEF), in line with their shared mandate as co-custodians of SDG indicator 8.7.1. To measure child labour, the 2024 Global Estimates adopt the statistical measurement framework set forth by the 18th International Conference of Labour Statisticians (ICLS) in 2008. These standards, which were also applied in previous editions of the Global Estimates, establish the statistical definition of child labour and its components.

This edition draws on data from 107 countries, representing approximately 60 per cent of the global population of children aged 5 to 17 years. To account for countries without available data, an explicit imputation strategy was used. This approach predicts child labour values using real observed data alongside sociodemographic covariates. Unlike simple regional averaging, the modelling approach offers several advantages, particularly by addressing the non-random nature of missing data.

The methodological report is organized as follows: section 2 outlines the statistical framework used in the estimates; section 3 describes the data sources; section 4 explains the harmonization of national data to ensure cross-country comparability; section 5 describes the imputation strategy for countries and age groups with missing data; section 6 concludes.

2. MEASUREMENT FRAMEWORK

The framework used to measure child labour in the 2024 Global Estimates aligns with the resolution concerning statistics of child labour adopted by the 18th ICLS in 2008. This is the same measurement framework that has been applied for the production of previous Global Estimates.

In 2018, the 20th ICLS adopted a revised resolution updating the statistical standards for measuring child labour.[1] While many countries have now aligned data collection with the new statistical standards, the 2008 framework has been retained in this edition to ensure comparability with previously published estimates. As more countries adopt the new measurement framework, the feasibility of transitioning to the updated framework for future Global Estimates will be evaluated.

A detailed overview of the statistical measurement framework is provided in the following sections.

2.1 Regional classifications

The primary regional classification used to present regional estimates is the system employed for monitoring the Sustainable Development Goals (SDGs). However, some regional figures are instead presented by ILO regions. The main report includes a statistical annex presenting results disaggregated by SDG, ILO, and UNICEF regional classifications.

2.2 Age of child

According to the ICLS framework, the age group targeted for child labour measurement includes all children aged 5 to 17 years, with age defined as the number of completed years at the child's last birthday. In the main report, results are presented

1 Resolution to amend the 18th ICLS Resolution concerning statistics of child labour.

for children aged 5 to 17 years, with further breakdowns provided for three distinct age groups: 5–11, 12–14, and 15–17 years.

2.3 Children in employment

Children in employment are all children who are "engaged in any activity falling within the production boundary in the United Nations System of National Accounts for at least one hour during the reference period". Activities within the System of National Accounts (SNA) production boundary – therefore considered as employment – include the production of goods and services for pay or profit, the production of goods for own use, unpaid trainee work, and volunteer work involving the production of goods. In contrast, unpaid household services (such as cooking and cleaning for one's own household) are not included within the SNA production boundary. Likewise, activities such as begging and stealing are excluded from the definition of employment, as they do not result in the production of goods or services.

To better measure the full range of SNA forms of work, some countries have now included dedicated modules on own-use production in national labour force surveys. Previously, such work was captured through more general questions about all work activities. The explicit inclusion of questions on own-use production of goods enables a more accurate understanding and measurement of the time individuals spend on these activities, which often account for a significant share of their working hours. It is important to note that while own-use production of goods has always been included in the measurement framework for child labour in the Global Estimates, the explicit incorporation of these questions in certain data sources may affect the comparability of results between this and previous editions.

2.4 General production boundary

Work within the general production boundary includes both employment and other productive activities. This means that it encompasses all activities falling under the SNA production boundary, as well as unpaid household services. Unpaid household services refer to "the production of domestic and personal services by a household member for consumption within their own household", commonly called "household chores". It is important to note that activities such as begging and stealing are not included within the general production boundary.

2.5 Child labour

As defined by the 18th ICLS, children are in child labour if "during a specified time period, [they] were engaged in one or more of the following categories of activities: (a) worst forms of child labour …; (b) employment below the minimum age …; and (c) hazardous unpaid household services".

In the main report, the principal figures on child labour are reported considering only activities within the SNA production boundary, that is, excluding hazardous unpaid household services. However, where indicated, results are also provided for child labour within the general production boundary, which includes hazardous unpaid household services.

According to the ILO Worst Forms of Child Labour Convention, 1999 (No. 182), the worst forms include all forms of slavery and trafficking, the recruitment of child soldiers, the use of children in prostitution or other illicit activities, and hazardous work performed by children. Using conventional household surveys, only hazardous work by children can be reasonably measured.

The minimum age for admission to employment or work, as established by the ILO Minimum Age Convention, 1973 (No. 138), is 15 years, although it allows for flexibility based on the national context. The Convention also permits countries to make exceptions for children aged 12 to 14 years to undertake "light work", which is work that is not harmful to the development of the child. Light work is defined at national level and typically establishes a maximum number of working hours per week for children aged 12 to 14 years, often along with other conditions about the type of work that can be performed, the times of day, and other elevant protections.

2.6 Hazardous work by children

Hazardous work is defined as "work which, by its nature or the circumstances in which it is carried out, is likely to harm the health, safety or morals of children". According to the ILO Worst Forms of Child Labour Recommendation, 1999 (No. 190), countries should consider the following conditions when establishing national hazardous work legislation:

(a) work which exposes children to physical, psychological or sexual abuse;
(b) work underground, under water, at dangerous heights or in confined spaces;
(c) work with dangerous machinery, equipment and tools, or which involves the manual handling or transport of heavy loads;
(d) work in an unhealthy environment which may, for example, expose children to hazardous substances, agents or processes, or to temperatures, noise levels, or vibrations damaging to their health;
(e) work under particularly difficult conditions such as work for long hours or during the night or work where the child is unreasonably confined to the premises of the employer.

For the purposes of the Global Estimates, hazardous work is measured using three dimensions: (a) work in hazardous occupations; (b) work in hazardous industries; and (c) work for long hours.

The industries and occupations considered as hazardous are defined based on the criteria outlined in ILO Recommendation No. 190. In the Global Estimates measurement framework, hazardous industries are mining and quarrying and construction.[2]

Regarding hazardous occupations, the ILO initially, during the publication of the first Global Estimates, identified 39 occupations classified as hazardous based on the four-digit ISCO-88 occupation codes of the International Standard Classification of Occupations (ISCO). These occupations have now been updated using ISCO-08, the latest international occupational classification system, and now include 41 occupations at the 3-digit ISCO-08 level.[3]

Finally, for the measurement of long hours, hazardous work is defined as work for 43 hours or more per week. Most national legislation on child labour establishes thresholds between 40 and 44 hours per week as the maximum number of hours children may work, making 43 hours a natural midpoint for international measurement.

2.7 Hazardous unpaid household services

As mentioned above, hazardous unpaid household services are included in the definition of child labour when it is measured based on the general production boundary. According to the 18th ICLS Resolution II, hazardous unpaid household services are those performed in the child's own household (a) for long hours; (b) in an unhealthy environment, involving unsafe equipment or heavy loads; (c) in dangerous locations; or that involve other similar risks.

2 These industries are classified by the International Standard Industrial Classification (ISIC) revision 4 on the 1-digit level. Under ISIC revision 4 "mining and quarrying" is coded as section B and "construction" as section F.

3 The full list of occupations included in the list of hazardous occupations at the 3- and 4-digit ISCO-08 level can be found in Annex 1.

However, current data sources on the conditions faced by children performing unpaid household services are limited. As a result, the only hazardous condition that can be reliably and comparably measured and estimated at the global level is work performed for long hours.

2.8 Operational definition of child labour

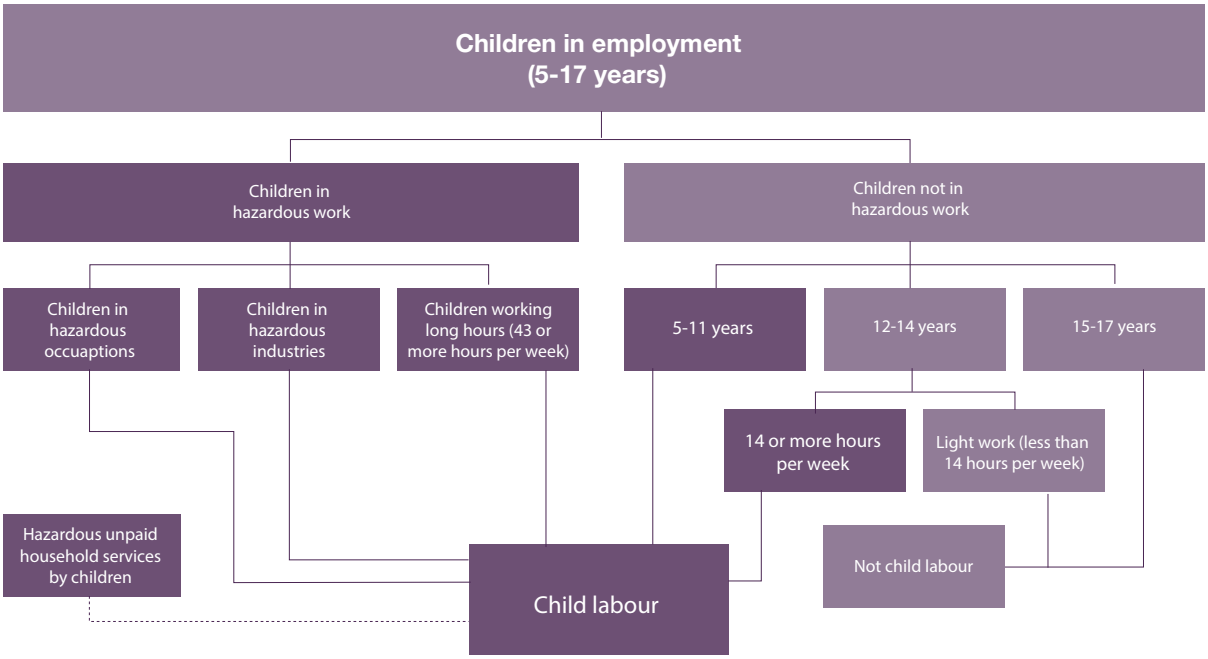
Using the principles outlined above, child labour indicators are systematically constructed for each country. To measure child labour, it is necessary first to establish whether a child aged 5 to 17 years is in employment. Once this is determined, it must then be assessed whether the child is working in hazardous work, by checking if they are working in a hazardous occupation, or in a hazardous industry, or for long hours.

It is important to note that these three categories of hazardous work are not mutually exclusive – a child may simultaneously work in a hazardous occupation, in a hazardous industry, and for long hours, or any combination of these. Any child in hazardous work is classified as being in child labour. For children in employment but not in hazardous work, the child's age must be considered to determine whether they are in child labour:

- **Children aged 5 to 11 years** who are in employment for at least one hour per week are classified as being in child labour, as they are under the minimum age for employment.
- **Children aged 12 to 14 years** in employment but not in hazardous work must be assessed based on their working hours. Those working more than 14 hours a week are classified as being in child labour. Employment under 14 hours a week is considered as permissible light work. Employment for 14 hours per week translates into an average of 2 hours per day in non-hazardous industries and occupations.
- **Children aged 15 to 17 years** in employment but not in hazardous work are not considered to be in child labour. Accordingly, for this age group, the number of children in child labour is equivalent to the number in hazardous work. This framework is presented in figure 1.

The main definition of child labour, as outlined above, considers only activities within the SNA production boundary. The statistical framework established by the 18th ICLS also provides guidelines for measuring child labour within the broader general production boundary. Child labour within this boundary includes all children identified as being in child labour based on the SNA production boundary, as well as children in hazardous unpaid household services. Children are considered to be performing hazardous unpaid household services if they are aged 5 to 14 years and work 21 or more hours per week in unpaid household activities.

Figure 1. Measurement framework for child labour



3. NATIONAL DATASETS

The 2024 Global Estimates of Child Labour are based on data from 107 countries (see Annex 2). While this edition uses nearly the same number of datasets as the previous edition, the age coverage of the underlying data has significantly improved, enabling the generation of more precise estimates.

3.1 Data sources

Data are drawn from a variety of sources. For 19 countries, data are from national Multiple Indicator Cluster Surveys (MICS) implemented with UNICEF support. For 37 countries, data are from either national child labour surveys conducted with ILO assistance or national labour force surveys that collected data on children aged 5 years and older. For two countries, data are from Demographic and Health Surveys. Data for the remaining 49 countries comprise either national labour force surveys or other household surveys that cover only part of the population group aged 5 to 17 years. The following sections provide detailed information on each type of data source.

3.2 Child labour surveys

Child labour surveys are conducted by countries with technical support and guidance from the ILO. They may take various forms but are typically either modules integrated into larger labour force surveys or stand-alone surveys targeting a representative sample of households. For stand-alone surveys, the sample size generally ranges from 5,000 to 15,000 households, whereas modular child labour surveys utilize the sample size of the broader survey.

These surveys provide nationally representative data – and often regionally representative data – on the prevalence of child labour. Child labour surveys also offer detailed socio-demographic information on children in child labour, aiding policymakers in identifying populations of children at the highest risk and the factors contributing to child labour. A key feature of child labour surveys is their collection of critical information on the types of work children perform and the working conditions they encounter.

3.3 Labour force and other household surveys

Labour force surveys are statistical instruments implemented by national statistical offices to gather data on the employment status, work patterns and economic activity of a country's population. They provide essential labour market indicators such as employment rates, unemployment rates, workforce participation and demographic breakdowns by surveying a large sample of households.

While many labour force surveys collect data from individuals aged 15 years and older, some also gather information on younger children, depending on the survey design. Labour force surveys typically collect detailed information on work activities, working hours, and industry and occupation of employment. These indicators can be used to estimate child labour.

Other national household surveys often collect similar data to labour force surveys. Other types of national surveys used in the Global Estimates of Child Labour include surveys on living conditions, household budget surveys, and household income and expenditure surveys.

3.4 Multiple Indicator Cluster Surveys (MICS)

MICS is an international household survey programme developed by UNICEF in the mid-1990s. Surveys are implemented by national statistical offices with technical support and guidance from UNICEF. MICS is designed to collect statistically sound and internationally comparable data on children, adolescents and their families for over 100 indicators of well-being, ranging from health and education to child labour. Since its initiation, more than 400 MICS have been conducted across more than 120 countries worldwide.

The most recent round of MICS (MICS7) includes a dedicated child labour module as part of the "Questionnaire for children and adolescents aged 5-17 years" with 13 questions on children's involvement in work activities. These questions cover children's participation in economic activities, fetching water, collecting firewood and unpaid household services, as well as the hours spent on these activities. MICS also gather information on hazardous work conditions.

3.5 Demographic and Health Surveys

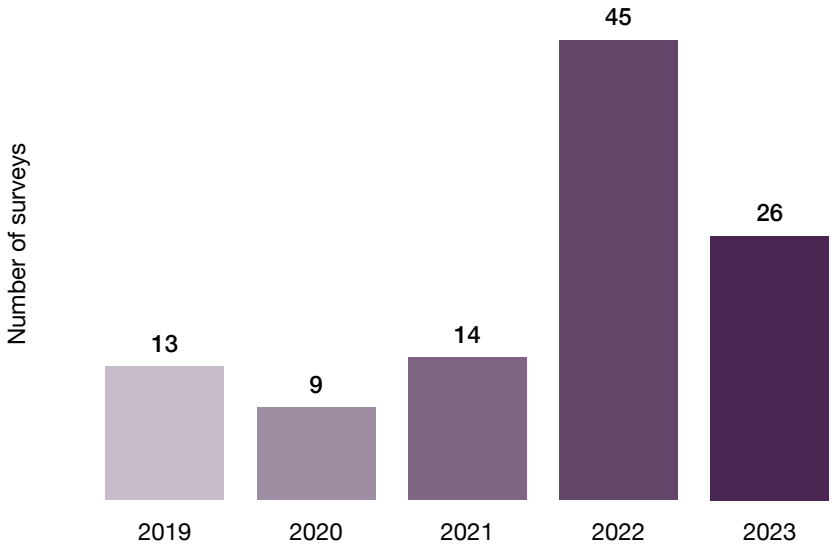
Demographic and Health Surveys are designed to collect national data on health, nutrition and household characteristics. They have been implemented in more than 90 countries and are typically conducted on large sample sizes ranging from 5,000 to 30,000 households. Some Demographic and Health Surveys incorporate the child labour module developed by MICS, which can be used to measure children's involvement in work and identify cases of child labour.

3.6 Timing of surveys

Nearly 90 per cent of the surveys used to produce the 2024 Global Estimates of Child Labour were conducted within the reference period from 2020 to 2024. While many countries collected nationally representative data suitable for calculating child labour during this period, a significant number did not. To increase data coverage, 13 surveys from one year prior to the reference period (i.e., 2019) were also included. Figure 2 presents the breakdown of surveys by year.

If multiple surveys were available for a particular country, the most recent survey that offered the most comprehensive coverage across all relevant age groups and was available at the time of data analysis for the estimates was selected for inclusion.

Figure 2. Number of surveys by year



3.7 Coverage of survey data

The 107 datasets used for the estimates cover 60 per cent of the global population of children aged 5 to 17 years. This represents a significant improvement over the 2020 edition, which covered only 46 per cent of children in this age group worldwide. Table 1 displays data coverage both globally and by region.

There are substantial differences in coverage across regions. Africa, particularly Sub-Saharan Africa, stands out as the region with the largest data availability – nearly 83 per cent of children in these countries are represented in the available datasets. This strong data foundation significantly enhances the reliability of the regional estimates.

Countries in Latin America and the Caribbean, as well as Asia and the Pacific, have also achieved notable data coverage, with nearly three quarters of children aged 5 to 17 years covered in Latin America and the Caribbean, and 57 per cent in Asia and the Pacific. Europe and Central Asia has the lowest data coverage of any region, primarily due to a lack of survey data for children aged 5 to 14 years.

Table 1. Data coverage by ILO regions

Region	Number of countries with data on any age group		% of countries with data on any age group		% of population aged 5 to 17 years covered, accounting for age coverage	
	2020	2024	2020	2024	2020	2024
Africa	31	39	57.4	72.2	56.1	82.8
Sub-Saharan Africa	29	36	61.7	76.6	54.5	82.9
Americas	19	21	57.6	63.6	52.1	57.1
Latin America and the Caribbean	18	20	58.1	64.5	74.6	72.6
Arab States	2	6	16.7	50.0	35.9	37.8
Asia and the Pacific	15	23	38.5	59.0	46.9	56.6
Europe and Central Asia	38	18	74.5	35.3	7.3	16.8
World	**105**	**107**	**55.6**	**56.6**	**46.1**	**59.9**

4. HARMONIZATION

Once the datasets for the Global Estimates were identified, each dataset was analysed using the standardized definition of child labour described in section 2. Each dataset was individually processed to generate the variables required to estimate child labour. Drawing on survey documentation, such as the questionnaire and metadata on the data collection process, variables – including involvement in the labour market, hours worked per week, and industry and occupation of employment – were constructed in line with international definitions and standards. In cases where not all the necessary information was available to build the child labour variable, the variable was left undefined. The modelling process estimates child labour for three age groups, namely 5–11, 12–14, and 15–17 years, and defines child labour separately for each of these age groups. Therefore, if the available data did not cover the full age range of a particular age group, the value for that group was treated as missing and subsequently imputed. For example, if a survey collected data only for children aged 10 years and older, the child labour estimate for the 5–11 age group was left undefined, as children aged 5–9 years not included in the data.

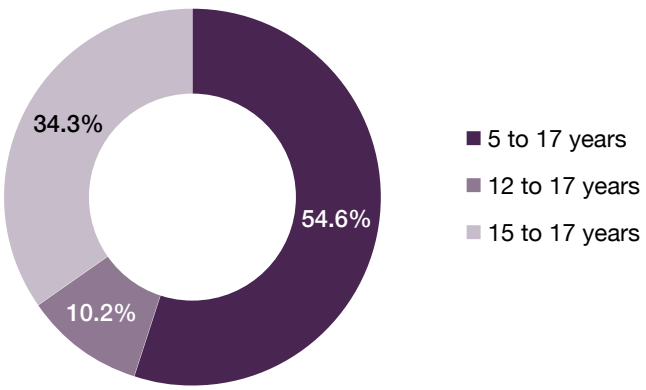
Regarding age coverage across datasets, 55 per cent of the datasets covered the entire age group from 5 to 17 years, as shown in figure 3.

5. MODELLING STRATEGY

While the data coverage for the 2024 Global Estimates represents three fifths of the global population of children, a statistical procedure was required to generate estimates for countries where data were missing. This step is particularly important because the absence of data is not random – that is, countries lacking data are often systematically different, and their data gaps are likely to be correlated with the prevalence of child labour. Failing to address these systematic patterns could result in biased estimates.

To mitigate this risk, an imputation strategy that relies on a series of econometric models to adjust for the non-random nature of missing data was applied. Through this process, child labour estimates are produced for countries with limited or no data, using available information on child labour, demographic indicators and other relevant contextual variables.

Figure 3. Age coverage of the data used in the 2024 Global Estimates of Child Labour



The 2024 Global Estimates introduced two major methodological improvements over previous modelling strategies:

- the use of robust cross-validation procedures, including LASSO[4] and other regularization techniques, across a large set of candidate models;
- the incorporation of interdependencies between variables to better capture the complex dynamics underlying child labour.

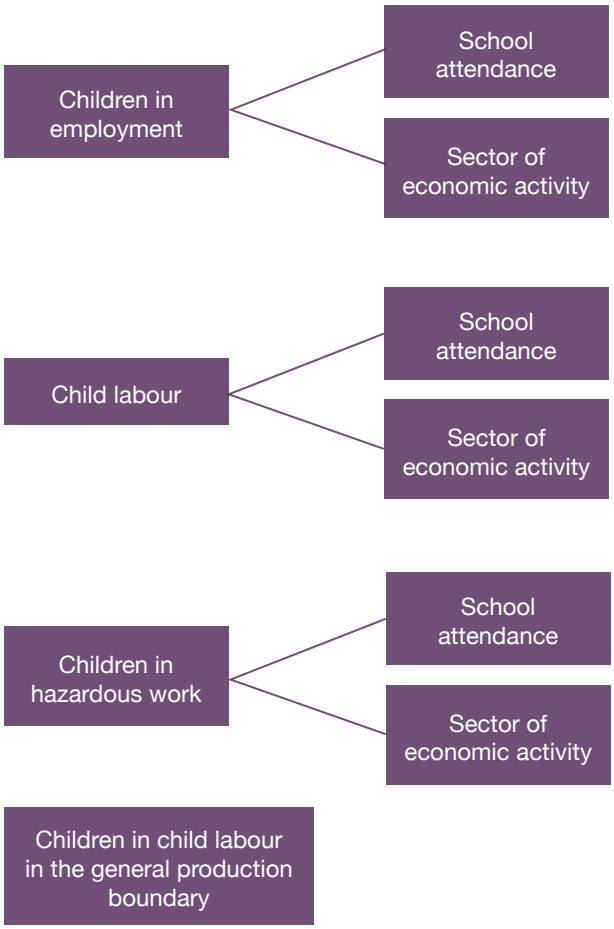
This section provides an overview of the methodology used to impute missing values for countries where no child labour data are available. In the following section, "real data" refers to the 107 empirical datasets used in the analysis, while "modelled data" refers to the imputed estimates of child labour and associated variables included in the report.

5.1 Overview of econometric models for imputation

The modelling procedure involved the creation of separate models for six key indicators. Four of these models imputed values for variables that correspond to rates: children in employment, child labour, children in hazardous work and children in child labour within the general production boundary. The remaining two models imputed values that correspond to disaggregated distributions of the population of children in employment, child labour and hazardous work. These models estimate the breakdown by sector of economic activity and school attendance.

Figure 4 provides a visual representation of the six models. Each model generated estimates disaggregated by sex (male, female, and total) and by age groups (5–11 years, 12–14 years, 15–17 years, and 5-17 years). This generated 12 observations within each country, although the categories are not independent, as the total values must equal the sum of their respective disaggregated components.

Figure 4. Indicators modelled in the 2024 Global Estimates



Each of the six models is built through a multi-step procedure that resulted in a complete dataset for each country. First, a dimension reduction procedure and cross-validation technique were executed to test various model specifications. This helped to identify the specification that predicted the values of the dependent variable with the highest accuracy. After the best-performing model was selected, the relationship between the dependent variable and the exogenous variables was established for countries with available data, using a linear regression model. Next, the model predicted the values of the dependent variable for countries with missing data, using data on the exogenous variables and the relationship established in the previous steps. Finally, a system

4 LASSO = Least Absolute Shrinkage and Selection Operator.

Table 2. Benchmark populations of each of the six modelled estimates

Indicator	Benchmark population
Children in employment	Population of children
Child labour	Population of children in employment
Children in hazardous work	Population of children in child labour
Children in child labour within the general production boundary	Population of children

of checks was carried out to ensure consistency in the estimates.

Each of the four rate indicators were modelled as a proportion (from 0 per cent to 100 per cent) of an underlying population. The underlying population is referred to as the "benchmark population". The benchmark population for each of the rate models are shown in table 2. After the proportions were modelled, the levels of each indicator was calculated by multiplying the modelled proportion by the benchmark population. For example, if boys aged 12 to 14 years in employment in a certain country was imputed to be 15 per cent, one can recover the implied number of boys aged 12 to 14 years in employment by multiplying 0.15 by the population of boys aged 12 to 14 years in that country.

Modelling indicators as a proportion of their benchmark population ensured that each imputation remained within its own respective logical boundary. For example, modelling child labour as a proportion of all children in employment ensured that the implied population of children in child labour given by the modelling process was not larger than the population of children in employment. Therefore, models were produced sequentially so that each new model was created using the results of the modelling of its benchmark indicator.

5.2 Model testing, cross-validation procedure and external variables used

5.2.1 Explanatory variables used in modelling

Modelled estimates were produced by applying econometric techniques to establish relationships between observed data and a set of external explanatory variables that are related to child labour selected on the basis of existing economic theory and empirical studies on the determinants of child labour. Data availability played a crucial role in the consideration of variables for their inclusion in the model, to balance the appropriateness of information and coverage of as many countries as possible. The explanatory variables considered in the modelling process were:

- Gross domestic product (GDP) per capita, purchasing power parity (PPP), constant 2021 international $
- SDG indicator 9.2.2: Manufacturing employment as a proportion of total employment (%)
- SDG indicator 8.5.2: Unemployment rate (%)
- SDG indicator 10.4.1: Labour income as share of GDP (%)
- SDG indicator 1.3.1: Proportion of population covered by social protection floors/systems (%)
- Youth not in employment, education or training by sex
- Employment numbers by various breakdowns:
  - Employment by sex and economic activity: ILO modelled estimates
  - Employment by sex and status in employment: ILO modelled estimates
  - Employment by sex and occupation: ILO modelled estimates

- Labour force data:
  - Labour force participation rate by sex and age: ILO modelled estimates
  - Unemployment by sex and age: ILO modelled estimates
  - Unemployment rate by sex and age: ILO modelled estimates
  - Combined rate of time-related underemployment and unemployment (LU2) by sex and age (%)
- Informal employment rate by sex and economic activity (%)
- Total social protection coverage (%): ILO modelled estimates
- Labour income distribution (7th–10th decile inclusive): ILO modelled estimates
- Agriculture, forestry and fishing, value added (% of GDP)
- Conflict data:
  - Internally displaced persons: new displacement associated with conflict and violence (number of cases)
  - Internally displaced persons: total displaced by conflict and violence (number of people)
- Sex ratio at birth (male births per female births)
- Education (% of GDP)
- Gini index
- Institutional quality variables:
  - Rule of law
  - Control of corruption estimates
  - Political stability and absence of violence or terrorism
- Exchange rate:
  - Official exchange rate
  - Terms of trade index
- Government expenditure on education (% of GDP)
- Trade (% of GDP)
- Credit card ownership (% age 15+)
- Fertility rate, total (births per woman)
- Life expectancy at birth, total (years)
- Mortality rate, infant (per 1,000 live births)
- Rate of urbanization: population by rural/urban areas
- Unemployment, youth total (% of total labour force aged 15–24)
- Education
  - Percentage of population aged 25+ with no schooling, both sexes
  - Percentage of population aged 25+ whose highest level of education is primary
- Several other population indicators:
  - Population aged 15–64 (% of total population)
  - Population aged 15–64, male (% of male population)
  - Population aged 15–64, female (% of female population)
  - Population aged 0–14 (% of total population)
  - Population aged 0–14, male (% of male population)
  - Population aged 0–14, female (% of female population)

5.2.2 Model selection

In the absence of theory guiding the decision of which and how many variables of those listed in section 5.2.1 to include in each model, statistical criteria were used to determine the best-performing model for each of the six indicators. Specifically, for each indicator, dimension reduction techniques were combined with cross-validation to select the most appropriate model specification in a two-step procedure described below.

First, a dimension reduction procedure was conducted. While a model that uses all available variables would maximize the fit of the model in the sample, such a model would not perform well in predicting observations out of the sample, which is exactly the objective of the imputation procedure. Therefore, it was necessary to identify the model dimensions that balance parsimony and fit. Smaller models impose fewer assumptions on the true data-generating process, while larger models enable a larger number of mechanisms and pathways through which variables affect child labour and related indicators. Furthermore, high correlations among explanatory variables could cause estimated coefficients to be noisy, which would affect the quality of the predicted values.

To determine the most appropriate dimension for each of the models, the adaptive LASSO estimator was applied to the full set of variables described above. The adaptive LASSO estimator

balances two objectives: (a) maximizing in-sample fit; and (b) penalizing model complexity in terms of the number of variables. The adaptive LASSO is a relatively recent estimator that can identify regression coefficients that are consistently close to zero, meaning they have little power in predicting the dependent variable. The adaptive LASSO drives coefficients that are otherwise close to 0 to exactly 0, dropping them from the model. In this way, the adaptive LASSO uses data-driven estimation to determine which variables should be included in the model.

After performing the adaptive LASSO methodology, a cross-validation procedure was employed using only the subset of variables identified as the most relevant predictors by the adaptive LASSO estimator. The adaptive LASSO yields a subset of many variables, some of which are highly correlated. For this reason, the cross-validation procedure tests approximately 20 different model specifications using different combinations of the variables from the subset given in the adaptive LASSO stage. The specifications range from "short" models that include only a few variables to larger models with more variables included.

Each of the different model specifications was then tested to determine which provided the best estimate on pseudo out-of-sample data. This was done by first randomly assigning approximately 70 per cent of the real data to the training set and 30 per cent of the data to a testing set. Then a linear regression was run using that particular specification and the 70 per cent of the data assigned to the training set. This yielded regression coefficients that are then used to predict the value of the indicator for the other 30 per cent of the data, the testing set. This procedure was performed 50 times for each specification. After the predicted values were obtained for the testing set, the predicted and real values of the dependant variable were compared, and the root mean square error over the 50 iterations was calculated. Finally, the model that yielded the "closest" estimates to the true values, as measured by the model with the lowest root mean squared error, was selected.

The modelling exercise consistently identified a core set of variables as the most influential across outcomes. These included labour market indicators such as youth labour force participation, NEET rates, youth and overall unemployment, and the share of employment in agriculture; economic indicators like GDP per capita and labour income for the 7th to 10th deciles; and social indicators such as social protection coverage, government education spending (as a share of GDP), fertility rate, urbanization, and the proportion of the population aged 15–24 years. Notably, the best-performing models repeatedly featured variables from this set, underscoring their central role in explaining the observed patterns.

5.3 Imputation procedures for rates

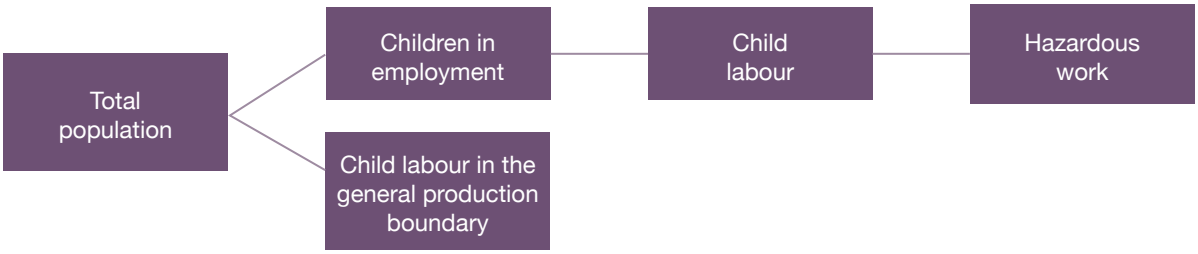
5.3.1 Population data

Before describing the modelling of rates, it is essential to understand the population data that underpin the modelling procedure. Population data underlie all the modelled estimates, as they are the benchmark for the children in employment model, which then serves as the benchmark for further models, as seen in table 2. Therefore, all indicators are directly or indirectly related to the population values. Population data come from the United Nations World Population Prospects (UN-WPP). The UN-WPP data contain values for the population of each country by single-year age group and sex. The aggregate age groups are then obtained by summing single-year age groups.

5.3.2 General procedures

Four of the six models for the 2024 Global Estimates involved the modelling of rates. These are the models of children in employment, child labour, children in hazardous work, and children in child labour in the general production boundary. Since some estimates are benchmarks for others, models were produced sequentially so that the relevant benchmark indicators were produced first. The sequence of the modelling of rates is shown in figure 5.

Figure 5. Sequence of modelling of rates



In preparing to conduct the modelling procedure, it was necessary to first extract the rates of each indicator from the 107 datasets available. This means that, for example, the rates of children in employment, child labour, hazardous work, and child labour in the general production boundary were extracted for each age group and sex breakdown, where available. These rates were then applied to UN-WPP data for 2024 for each sex and age disaggregation. The underlying assumption in this procedure is that the rates of each remain stable over reduced time intervals. After the rates were applied to each subcategory of the 2024 population data, a simple rebalancing procedure was executed to ensure consistency in the rates for the aggregate categories.

For example, if a country had data on child labour from 2022 that indicated that 10 per cent of girls and 20 per cent of boys are in child labour and the population of girls and boys is even (50 per cent girls and 50 per cent boys), the level of child labour in the total population is 15 per cent. However, if in 2024, the proportion of boys in the population rises to 60 per cent, the child labour rates in the total population will skew towards the child labour rate of boys, since they now make up a larger percentage of the population, as seen in table 3. Therefore, the rate in the total population will be adjusted to be 16 per cent instead of 15 per cent in order to be in alignment with the disaggregated rates. In reality, data differences in population make-up over short time intervals are much less dramatic than in the example; therefore, the rebalancing exercise of bringing total rates into alignment with rates by sex and age often only creates minute changes in the total figures.

Table 3. Example of the rebalancing procedure for real data sources

Sex	Rate of child labour in 2022	Population in 2024	Levels in 2024	Rate of child labour in 2024
Girls	10%	40	4	10%
Boys	20%	60	12	20%
Total	**15%**	**100**	**16**	**16%**

After rebalancing and extracting the data, a dataset was created that included indicators disaggregated by sex and age for countries where data are available. This dataset was then used to perform the previously described dimension reduction and cross-validation procedure. This step identified the best-performing model specification, which was used in the subsequent analysis. Once the optimal model was selected, linear regressions were run on the real data to determine the relationships between the indicator and the explanatory variables.

The regression takes the following form:

$$\left(\frac{Indicator}{Benchmark}\right)_{ijkr} = X_i(m)'\beta + \rho Sex_j + \kappa Age_k + \mu Region_r + \theta Region_r \times Sex_j + \psi Region_r \times Age_k + \epsilon_{ijkr}$$

In the above equation the subscript i represents a particular country, j refers to sex, k refers to a specific age group, while region r refers to the geographic region. The left-hand side expresses, for a given indicator, its level as a proportion of its benchmark. For instance, for the children in employment model, the left-hand side boils down to children in employment as a proportion of the total population. The vector of covariates $X_i(m)'\beta$ contains the variables belonging to the best-performing model based on the model selection procedure. These variables vary solely at the country level () and capture cross-country variation in macro indicators. In addition to capturing differences across countries, regional, sex and age fixed effects are included, along with interactions between region and sex as well as by region and age. Intuitively, this enables development of separate intercept terms for sex by region and age by region, which capture systematic differences within breakdowns and across regions. For instance, one could postulate that the child labour rates are quite different for girls in the 5–11 years age group in Latin America compared to boys in the 15–17 age group in Caribbean countries. This model is flexible enough to capture systematic differences in indicators across breakdowns, while being parsimonious enough to not be victim of poor out-of-sample performance due to overfitting problems. It is important to note that the regression models include all demographic and sex categories simultaneously, thereby increasing the degree of freedom in the estimation.

After this regression was run, the coefficients were extracted and used to predict the values of the indicator for countries with no available data.

Once predictions were generated, additional steps were necessary to ensure that the results remain consistent and logically sound. First, there was a check to ensure that predicted values were within logical limits (between 0 and 1). After this validation, a rebalancing step was performed to ensure that overall rates aligned with the weighted sum of the disaggregated rates by sex and age. For instance, the levels of child labour for all children aged 5–17 years must be equal to the sum of the levels for children aged 5–11, 12–14 and 15–17 years. Therefore, the rate of child labour for children aged 5–17 years was pinned down by the implied level of total children in child labour given by the summation of the levels in each of the sub-age categories.

5.3.3 Age group interdependencies

An important consideration when modelling rates is the interdependencies that exist between age groups. For example, the rate of children in employment of children aged 15–17 years is consistently observed to be greater than that of children aged 12–14 or 5–11 years. This makes logical sense, as one would expect that a higher proportion of children aged 15–17 years are working in employment in a given country than their younger counterparts. It is therefore essential that modelled estimates maintain these relationships.

However, maintaining and exploiting such interdependencies becomes complex when countries have data missing for some age groups within a country. For example, if data exist for a particular country on the rate of children in employment for the 15–17 age group, it would be prudent to use this information in the modelling of the rates for the younger two age categories. Doing so allows the model to capture underlying

relationships between age groups – relationships that are influenced by shared country-specific factors that may not be otherwise observed by the econometrician.

In order to capture and exploit age group dependencies that exist, the current modelling procedure included an auxiliary imputation procedure for the subset of countries with data missing for certain age groups. Note that this procedure was performed after the model selection, but before the imputation procedure on the full set of countries. This was carried out in the following way. Using the specification determined through the model selection step, a regression was run using the ratio of the given indicator between age groups as the dependent variable. Additionally, the indicator for the available age groups was added to the regression as an explanatory variable.

This regression is therefore given by the formula:

$$\left(\frac{indicator_{12-14}}{indicator_{15-17}}\right)_{ijkr} = X_i(m^*)'\beta + \rho_2 indicator_{15-17} + \mu Region_r + \theta Region_r \times Sex_j + \psi Region_r \times Age_k + \epsilon_{ijkr},$$

where the lower-case $indicator$ designates the rates of a given indicator for a given age group. Using the coefficients from this regression, the predicted values of $\left(\frac{\widehat{indicator_{12-14}}}{indicator_{15-17}}\right)_{ijkr}$ are calculated and then used to recover levels of $indicator_{12-14}$ for countries where data for age group 15–17 years are present, but data for age group 12–14 are not. A similar procedure was completed for the 5–11 age group.

At the end of this step, imputed values have been "filled in" for countries where data for certain age groups are missing. Importantly, this step was completed before the imputation procedure for the full set of countries where values are imputed for countries with no available data. Moreover, the imputed rates yielded in this step are then taken as real values during the execution of the full imputation procedure. Given the high in-sample correlation of rates across age groups in countries where data are available, this is seen as an innocuous assumption.

5.3.4 Imputation of children in employment

Children in employment was modelled using the child population as a benchmark. Specifically, the dependent variable was expressed as the percentage of children in employment out of the total number of children in the same sex and age group.

After performing dimension reduction and cross-validation to determine the model specification that best predicted children in employment, the auxiliary regression procedure described in section 5.3.3 was run for countries with data on some but not all age groups. Following this, the predicted values obtained for the missing age groups were incorporated into the real data and taken as real values to be used in the full imputation procedure. Then the full imputation procedure was conducted and results in predicted rates of children in employment for countries that have no data.

After the imputation is complete, predicted rates below 0 or above 1 are bounded and rebalancing was done to ensure internal consistency in the aggregated sex and age groups. These rates of children in employment were then used as the benchmark for the child labour model.

5.3.5 Imputation of child labour

The modelling procedure for child labour followed much the same process as that for children in employment, with one important addition. Child labour was modelled as a proportion of children in employment. The definition of child labour implies that the number of children in child labour is at most equal to the number of children in employment. Consequently, child labour as a proportion of children in employment is bounded between 0 and 1. Modelling child labour in this form imposed logical constraints directly within the estimation process.

It is important to note that child labour is equal to children in employment for children aged 5–11 years, meaning that child labour as a proportion of children in employment will be equal to 1 (100 per cent) for every country.

For some countries, data are insufficient to directly calculate child labour. However, the related indicator, noted here as SDG1 as it is the measurement of child labour used for Sustainable Development Goal (SDG) monitoring, *can* be calculated. SDG1 excludes the participation of children in hazardous industries or occupations from its measurement of child labour, making it a subset of the broader child labour definition used in the Global Estimates. Despite this, it remains closely related to overall child labour levels. To take advantage of the relationship between SDG1 and child labour – and to maximize the use of available data in countries where child labour figures are missing but SDG1 is available – an auxiliary regression was conducted prior to the model selection step.

Specifically, the following regression is estimated:

$$\left(\frac{CL}{CiE}\right)_{ijkr} = \alpha + \beta_1 \theta_{ijkr} + \beta_2 GDPpc_i + \epsilon_{ijkr},$$

where

$$\theta_{ijkr} \equiv \left(\frac{SDG1}{CiE}\right)_{ijkr},$$

where CL is child labour levels in country i, for sex j and k age group, and CiE is the level of children in employment. The coefficients for this regression were then used to predict the rate of child labour (as a percentage of children in employment). These predicted rates were then incorporated into the real data on child labour rates and treated the same as real values in the rest of the estimation procedure. This was seen as an acceptable assumption due to the close relationship between child labour and SDG1 rates.

Following this auxiliary step, the imputation process proceeded in the same way as the children in employment model. The model selection procedure was conducted, followed by the procedure to account for age dependencies and the imputation procedure for the set of all countries, and concluded by the rebalancing of aggregate categories. The imputation yielded a dataset of real and imputed values of child labour as a percentage of children in employment. Using these data and the results of the children in employment model, it was possible to recover the levels of child labour and the child labour rate in the population.

5.3.6 Imputation of hazardous work

Following the conclusion of the child labour model, the hazardous work model was constructed using child labour as the benchmark population. The definition of hazardous work implies that the number of children in hazardous work is at most equal to the number of children in child labour. Therefore, modelling hazardous work as a proportion of children in child labour established logical boundaries for the imputation process, similar to the child labour model. Notably, for children aged 15–17 years child labour and hazardous work are equal, meaning that the rate of hazardous work (hazardous work as a proportion of children in child labour) for this age group is equal to 1 for all countries.

A similar procedure to that for the children in employment and child labour models was utilized for hazardous work. A dimension reduction and cross-validation procedure was used to select the most appropriate model. This was followed by the implementation of that model specification into a regression with accounts for age dependencies. This process was followed by the regressions and imputation of hazardous work for countries with no data. Finally, bounding and rebalancing were carried out.

5.3.7 Imputation of child labour in the general production boundary

In the 2024 Global Estimates, the indicator of child labour in the general production boundary was also modelled. This indicator has a more expansive definition than that of the primary child labour indicator, in that the child labour measure in the general production boundary also includes hazardous household chores. For this reason, the benchmark for this indicator is the entire population of children, and the dependant variable modelled was child labour in the general production boundary rates as a proportion of the population of children.

The modelling procedure itself followed the same structure as the previous three models that involve rates.

5.4 Imputation procedures for distributions

This section describes the general modelling procedure for the two indicators modelled as distributions: sector of economic activity and school attendance. These indicators were modelled as breakdowns of children in employment, child labour and hazardous work. While the modelling procedure followed much the same logic as that for rates, distributional models require additional correction to ensure they preserve the logical bounds of estimation.

The general procedure followed the preceding structure. First, real data were extracted and rebalanced to ensure that aggregates are internally consistent. Then the model selection procedure was conducted through the same dimension reduction and cross-validation procedure used for the modelling of rates. Next, using the model specification determined through the model selection process, a regression was run to establish the relationship between the indicator and the explanatory variables. The coefficients from the regression were then used to impute missing observations. Finally, a multistep rebalancing procedure was executed.

Throughout this section the following notations are used. Allow to $f_{(d(b))}$ represent the fraction of the population b that has characteristic d, were b is either the population of children in employment, children in child labour, or children in hazardous work. For example, $f_{(attend(CL))}$ is the fraction of children in child labour who attend school. This will naturally be between 0 and 1 and within each age and sex category:

$$\sum_{d} f_{(d(b))} = 1$$

To initiate the modelling process, $f_{(d(b))}$ is recovered for each age and sex category of countries with available data. Using the same dimension reduction and cross-validation procedure as that for rates, different specifications of the follow equation are tested:

$$f_{ijkrd} = X_i'\beta + \rho Sex_j + \kappa Age_k + \mu Region_r + \gamma Breakdown_d + \alpha Age_k \times Breakdown_d + \Gamma sex_k \times Breakdown_d + \theta Region_r \times Breakdown_d + \epsilon_{ijkrd}$$

Note that for each b, each underlying population, the distributions are modelled separately. Estimating the distributions separately for children in employment, child labour and hazardous work allows us to have different effects of variables depending on the underlying benchmark population. Sex_j, Age_k , $Region_r$, and $Breakdown_d$ are dummies for the sex, age, region and the specific breakdown (for example, in the school attendance model $Breakdown_d$ would be either attending or not attending). Intuitively, breakdown*region dummies capture the idea that there are systematic (average) differences in the fraction of individuals in breakdown by region. The other two multiplicative variables allow similar variation by age and sex.

Once the best-performing specification was identified, a regression was run on the real data using the best identified specification, which will take a form of that in the equation above. From this regression estimated coefficients were identified and used to predict the values for countries with missing data. Since there are no clear empirical or theoretical interdependencies between the values for different age groups in these models, there is no auxiliary regression to account for interdependencies across age groups.

After obtaining the imputed values of estimates from the modelling, the results must be rebalanced to ensure internal consistency. First, it was ensured that the breakdowns of each distribution add to 100 per cent with respect to the benchmark. For example, the percentage of children in child labour attending school and the percentage of children in child labour not attending school must sum to 100 per cent. In order to resolve cases where this does

not hold, an adjustment factor was calculated using the following procedure, using school attendance as an example.

First the predicted populations of children in employment attending and not attending school are calculated:

$$\widehat{f_{\text{NA}}}(CiE) \times CiE_{2024} = \widehat{NA_{2024}}$$

$$\widehat{f_{A}}(CiE) \times CiE_{2024} = \widehat{A_{2024}},$$

where $\widehat{f_{\text{NA}}}(CiE)$ is the modelled proportion of children in employment not attending school, $\widehat{f_{A}}(CiE)$ is the modelled proportion attending school and CiE_{2024} is the population of children in employment. This yields $\widehat{NA_{2024}}$, the predicted population of children in employment who do not attend school, and $\widehat{A_{2024}}$, the predicted population of children in employment who attend school. Summing these factors we get $\widetilde{CiE_{2024}}$, which is the implied predicted level of children in employment.

$$\widehat{NA_{2024}} + \widehat{A_{2024}} = \widetilde{CiE_{2024}}$$

Usingand $\widetilde{CiE_{2024}}$ the real population of children in employment, CiE_{2024} the adjustment factor, ϕ, can be calculated from the following equation:

$$\frac{CiE_{2024}}{\widetilde{CiE_{2024}}} \equiv \phi,$$

such that:

$$\underbrace{\phi\widehat{NA_{2024}}}_{\text{Adjusted NA}} + \underbrace{\phi\widehat{A_{2024}}}_{\text{Adjusted A}} = CiE_{2024}$$

This allows the calculation of adjusted values of the modelled estimates and that yield levels that are in accordance with the benchmark levels.

$$\frac{\phi NA_{2024}}{CiE_{2024}} = \widehat{f_{\text{NA}}}(CiE)adjust$$

$$\frac{\phi A_{2024}}{CiE_{2024}} = \widehat{f_{\text{A}}}(CiE)adjust$$

After this first step of rebalancing is done, a further rebalancing was needed to ensure that the level of each disaggregated sex and age category add up to the levels for the total categories. This was done in a manner analogous to that of the indicators involving rates.

Finally, given that the modelling process was carried out separately for each benchmark population (children in employment, child labour and hazardous work), the final rebalancing ensured that the logical bounds across the breakdowns are respected as well. This implied, first, that the number of children in each category of the distribution (that is,) for children aged 5 to 11 years is identical between children in employment and child labour. The same holds between hazardous work and child labour for children aged 15 to 17 years. For other cases, it needs to be ensured that the levels of each category of children in employment are at least as high as those in child labour, and levels of children in child labour are at least as high as those in hazardous work.

The process of rebalancing to maintain logical bounds across distributions is explained in the example presented in table 4. In the example, the unconstrained estimation procedure yields imputed values that result in the implied number of children in child labour who are not attending school (110) exceeding the implied number of children in employment not attending school (100). However, this is not possible, since the population of children in child labour is a subset of that of children in employment. To ensure results are internally consistent, the number of children in child labour who are not attending school must be at most 100. In this example, the estimated population of children in child labour not attending school exceeds that of children in employment by 10 children, therefore the levels of children in child labour not attending school need to be adjusted by -10. Here, the difference between children in employment and child labour for those attending school is 20, therefore the 10 excess children not attending school are reclassified as attending school. This results in levels in child labour that are internally consistent. Furthermore, given that the reallocation

Table 4. Adjustments to ensure consistency between children in employment and child labour for the breakdown of school attendance

School attendance	Estimated levels of children in employment	Estimated levels of child labour	Adjustment required	Adjusted levels of child labour
Not attending school	100	110	–10	100
Attending school	100	80	+10	90

process only redistributes observations, the sum of children not attending school and attending school in child labour still equals the original child labour benchmark.

The same type of procedure was conducted for the model on the sector of economic activity, an example of which is presented in table 5. In this instance, the number of children in child labour working in the industry sector implied by the modelled estimates exceeds that of children in employment by 100 observations. To ensure internal consistency, these 100 observations are allocated across the other two categories by distributing them proportionally to the relative adjustment available in that category, where the relative adjustment available is given by

$$\left(\frac{AdjustmentAvailable_d}{\sum_d \text{Adjustment}Available_d} * 100\right).$$

For the two indicators classified as distributions, the estimated levels of child labour were first adjusted to be, at most, equal to those of children in employment. Then the estimated levels of hazardous work were adjusted to be, at most, equal to those of the revised values of child labour. This stepwise process ensured that the levels of hazardous work were also, at most, equal to those of children in employment.

While these examples illustrate large rebalancing effects for simplicity, in practice the rebalancing procedure results in only minor adjustments to most imputations. Once this final rebalancing step was completed, the full dataset – comprising both imputed and observed values for the distributions of the three benchmark populations – was finalized.

6. EVALUATION OF THE METHODOLOGY

To evaluate the robustness of the estimates produced, it is important to understand how they could differ if a different sample of countries was used. One way to evaluate this uncertainty is by calculating the standard deviation of the estimates at both regional and global levels, providing a measure of their sensitivity to sampling variability.

Table 5. Adjustments to ensure consistency between children in employment and child labour for sector of economic activity

Economic sector	Estimated levels of children in employment	Estimated levels of child labour	Adjustment available	Adjustment required	Adjusted levels of child labour
Agriculture	100	50	+50	100*(50/100)=50	100
Services	100	50	+50	100*(50/100)=50	100
Industry	100	200	-100	-100	100

Table 6. Standard deviation of the global and regional estimates for children in employment

	Estimated number of children aged 5 to 17 years in economic activity (thousands)	Estimated rate of economic activity for children aged 5 to 17 years	Standard deviation (% points)	Coefficient of variation (CV)
World	229,215	13.0%	0.58	4.5%
Africa	151,137	31.7%	1.50	4.7%
Sub-Saharan Africa	140,220	34.7%	1.71	4.9%
Americas	14,849	7.7%	0.31	4.0%
Latin America and the Caribbean	11,328	8.5%	0.43	5.1%
Arab States*	4,596	9.1%	-	-
Asia and the Pacific	49,699	5.6%	0.86	15.4%
Europe and Central Asia	8,935	6.0%	0.46	7.7%

Note: * Due to the limited number of surveys available from countries in the Arab States, it is not possible to calculate the standard deviation for this region.

However, this method does not capture unknown biases in the modelling process or uncertainties associated with the input data.

To estimate the variability related specifically to sampling, the estimates of children in employment were assessed using a resampling approach. This involved running the modelling procedure 150 times, each time randomly excluding approximately 15 per cent of countries from the sample. The resulting distribution of estimates was then used to calculate the standard deviation at both global and regional levels. Table 6 summarizes the results of this analysis.

The coefficient of variation provides valuable insight into the relative precision of the regional estimates. In most regions—including Africa, the Americas, Latin America and the Caribbean, Sub-Saharan Africa, and Europe and Central Asia—the CVs remain below 10 per cent, indicating acceptable to very good precision and relatively low sensitivity to changes in the country sample.

In contrast, the estimate for Asia and the Pacific exhibits a higher CV of 15 per cent, reflecting a lower level of precision and a greater degree of uncertainty relative to the estimated rate of child economic activity. This likely stems from greater variability in national data or higher sensitivity of the modelling process in this region.

For the Arab States, it was not possible to calculate a coefficient of variation due to the limited number of recent, comparable surveys available from countries in the region. This lack of data makes it difficult to assess the stability of the estimates and underscores the need for expanded and regular survey implementation to ensure more robust and representative results in future rounds.

Overall, the results indicate that the estimates are generally robust. At the same time, they highlight the importance of continued efforts to strengthen survey coverage—particularly in regions such as Asia and the Pacific and the Arab States, where data limitations contribute to higher uncertainty or prevent a full assessment of precision.

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ANNEXES

Annex 1. Hazardous occupations and industries

Table A1: Hazardous occupations at ISCO-08 three-digit level

ISCO-08 Code	ISCO-08 Minor Group Title
223	Traditional and complementary medicine professionals
224	Paramedical practitioners
226	Other health professionals
312	Mining, manufacturing and construction supervisors
312	Process control technicians
321	Medical and pharmaceutical technicians
322	Nursing and midwifery associate professionals
324	Veterinary technicians and assistants
325	Other health associate professionals
352	Telecommunications and broadcasting technicians
541	Protective services workers
621	Forestry and related workers
622	Fishery workers, hunters and trappers
711	Building frame and related trades workers
712	Building finishers and related trades workers
721	Sheet and structural metal workers, moulders and welders, and related workers
722	Blacksmiths, toolmakers and related trades workers
723	Machinery mechanics and repairers
731	Handicraft workers
741	Electrical equipment installers and repairers
742	Electronics and telecommunications installers and repairers
754	Other craft and related workers
811	Mining and mineral processing plant operators
812	Metal processing and finishing plant operators
813	Chemical and photographic products plant and machine operators
814	Rubber, plastic and paper products machine operators
815	Textile, fur and leather products machine operators
816	Food and related products machine operators
817	Wood processing and papermaking plant operators

ISCO-08 Code	ISCO-08 Minor Group Title
818	Other stationary plant and machine operators
821	Assemblers
832	Car, van and motorcycle drivers
833	Heavy truck and bus drivers
834	Mobile plant operators
835	Ships' deck crews and related workers
921	Agricultural, forestry and fishery labourers
931	Mining and construction labourers
933	Transport and storage labourers
951	Street and related services workers
961	Refuse workers
962	Other elementary workers

Table A2. Hazardous occupations at ISCO-08 four-digit level

ISCO-08 Code	ISCO-08 Unit Group Title
2240	Paramedical practitioners
2230	Traditional and complementary medicine professionals
2264	Physiotherapists
2265	Dieticians and nutritionists
2266	Audiologists and speech therapists
2267	Optometrists and ophthalmic opticians
2269	Health professionals not elsewhere classified
3121	Mining supervisors
3122	Manufacturing supervisors
3123	Construction supervisors
3131	Power production plant operators
3132	Incinerator and water treatment plant operators
3133	Chemical processing plant controllers
3134	Petroleum and natural gas refining plant operators
3135	Metal production process controllers
3211	Medical imaging and therapeutic equipment technicians
3213	Pharmaceutical technicians and assistants
3214	Medical and dental prosthetic technicians
3221	Nursing associate professionals
3222	Midwifery associate professionals

ISCO-08 Code	ISCO-08 Unit Group Title
3240	Veterinary technicians and assistants
3251	Dental assistants and therapists
3253	Community health workers
3254	Dispensing opticians
3255	Physiotherapy technicians and assistants
3256	Medical assistants
3257	Environmental and occupational health inspectors and associates
3259	Health associate professionals not elsewhere classified
3431	Photographers
3521	Broadcasting and audio-visual technicians
5212	Street food salespersons
5243	Door-to-door salespersons
5244	Contact centre salespersons
5411	Fire fighters
5412	Police officers
5413	Prison guards
5414	Security guards
5419	Protective services workers not elsewhere classified
6210	Forestry and related workers
6221	Aquaculture workers
6222	Inland and coastal waters fishery workers
6223	Deep-sea fishery workers
6224	Hunters and trappers
7111	House builders
7112	Bricklayers and related workers
7113	Stonemasons, stone cutters, splitters and carvers
7114	Concrete placers, concrete finishers and related workers
7115	Carpenters and joiners
7119	Building frame and related trades workers not elsewhere classified
7121	Roofers
7122	Floor layers and tile setters
7123	Plasterers
7124	Insulation workers
7125	Glaziers
7126	Plumbers and pipe fitters

ISCO-08 Code	ISCO-08 Unit Group Title
7127	Air conditioning and refrigeration mechanics
7211	Metal moulders and coremakers
7212	Welders and flamecutters
7213	Sheet-metal workers
7214	Structural-metal preparers and erectors
7215	Riggers and cable splicers
7221	Blacksmiths, hammersmiths and forging press workers
7222	Toolmakers and related workers
7223	Metal working machine tool setters and operators
7224	Metal polishers, wheel grinders and tool sharpeners
7231	Motor vehicle mechanics and repairers
7232	Aircraft engine mechanics and repairers
7233	Agricultural and industrial machinery mechanics and repairers
7234	Bicycle and related repairers
7311	Precision-instrument makers and repairers
7312	Musical instrument makers and tuners
7313	Jewellery and precious-metal workers
7314	Potters and related workers
7315	Glass makers, cutters, grinders and finishers
7316	Sign writers, decorative painters, engravers and etchers
7411	Building and related electricians
7412	Electrical mechanics and fitters
7413	Electrical line installers and repairers
7421	Electronics mechanics and servicers
7422	Information and communications technology installers and servicers
7541	Underwater divers
7542	Shotfirers and blasters
7549	Craft and related workers not elsewhere classified
8111	Miners and quarriers
8112	Mineral and stone processing plant operators
8113	Well drillers and borers and related workers
8114	Cement, stone and other mineral products machine operators
8121	Metal processing plant operators
8122	Metal finishing, plating and coating machine operators
8131	Chemical products plant and machine operators

ISCO-08 Code	ISCO-08 Unit Group Title
8141	Rubber products machine operators
8142	Plastic products machine operators
8143	Paper products machine operators
8151	Fibre preparing, spinning and winding machine operators
8153	Sewing machine operators
8154	Bleaching, dyeing and fabric cleaning machine operators
8155	Fur and leather preparing machine operators
8156	Shoemaking and related machine operators
8157	Laundry machine operators
8159	Textile, fur and leather products machine operators not elsewhere classified
8160	Food and related products machine operators
8171	Pulp and papermaking plant operators
8172	Wood processing plant operators
8181	Glass and ceramics plant operators
8182	Steam engine and boiler operators
8183	Packing, bottling and labelling machine operators
8189	Stationary plant and machine operators not elsewhere classified
8211	Mechanical machinery assemblers
8212	Electrical and electronic equipment assemblers
8219	Assemblers not elsewhere classified
8321	Motorcycle drivers
8322	Car, taxi and van drivers
8331	Bus and tram drivers
8332	Heavy truck and lorry drivers
8341	Mobile farm and forestry plant operators
8342	Earthmoving and related plant operators
8343	Crane, hoist and related plant operators
8344	Lifting truck operators
8350	Ships' deck crews and related workers
9211	Crop farm labourers
9212	Livestock farm labourers
9213	Mixed crop and livestock farm labourers
9214	Garden and horticultural labourers
9215	Forestry labourers
9216	Fishery and aquaculture labourers

ISCO-08 Code	ISCO-08 Unit Group Title
9311	Mining and quarrying labourers
9312	Civil engineering labourers
9313	Building construction labourers
9331	Hand and pedal vehicle drivers
9332	Drivers of animal-drawn vehicles and machinery
9333	Freight handlers
9334	Shelf fillers
9510	Street and related service workers
9520	Street vendors (excluding food)
9611	Garbage and recycling collectors
9612	Refuse sorters
9613	Sweepers and related labourers
9621	Messengers, package deliverers and luggage porters
9622	Odd job persons
9623	Meter readers and vending-machine collectors
9624	Water and firewood collectors
9629	Elementary workers not elsewhere classified
9312	Civil engineering labourers

Annex 2. Data sources

Table A.3 List of data sources used in the 2024 Global Estimates of Child Labour

Country	Data source	Year
Afghanistan	MICS	2023
Albania	LFS	2022
Algeria	MICS	2019
Angola	IEA	2021
Argentina	EPH	2023
Austria	LFS	2023
Bangladesh	NCLS	2022
Barbados	LFS	2019
Belarus	LFS	2022
Belize	LFS	2023
Benin	MICS	2022
Bhutan	LFS	2022
Bolivia (Plurinational State of)	ECE	2023
Botswana	MTHS	2023
Burkina Faso	NCLS	2022
Burundi	ECVM	2020
Brazil	PNADCCL	2022
Brunei Darussalam	LFS	2023
Cambodia	HSES	2021
Central African Republic	MICS	2019
Chad	MICS	2019
Chile	ENE	2023
Colombia	ENTI	2022
Comoros	MICS	2022
Congo	SWTS	2022
Costa Rica	ENAHO	2022
Côte d'Ivoire	ECVM	2022
Democratic Republic of the Congo	EGI	2020
Ecuador	ENEMDU	2022
Egypt	NCLS	2021
El Salvador	EHPM	2023
Estonia	LFS	2022

Country	Data source	Year
Eswatini	MICS	2022
Ethiopia	NLFS	2021
Fiji	MICS	2021
France	EE	2022
Gabon	DHS	2021
Gambia	LFS	2023
Georgia	LFS	2022
Ghana	HIES	2022
Greece	LFS	2022
Guatemala	ENEI	2022
Guinea-Bissau	ECHVM	2022
Guyana	MICS	2020
Honduras	ENTIH	2023
Hungary	LFS	2022
India	PLFS	2023
Indonesia	LFS	2023
Iran (Islamic Republic of)	LFS	2022
Iraq	LFS	2021
Jamaica	MICS	2022
Jordan	LFS	2021
Kenya	CHS	2021
Lao People's Democratic Republic	LFS	2022
Lebanon	LFS	2019
Liberia	DHS	2020
Madagascar	EPM	2022
Malawi	IHS	2020
Maldives	HIES	2019
Mali	EMOP	2020
Mauritania	ECVM	2019
Mauritius	CMPHS	2022
Mexico	ENTI	2022
Mongolia	NCLS	2022
Myanmar	LFS	2020
Niger	ECVM	2022
Nigeria	NCFLS	2022

Country	Data source	Year
North Macedonia	MICS	2019
Pakistan	LFS	2021
Panama	EML	2023
Paraguay	EPHC	2023
Peru	EPEN	2023
Philippines	LFS	2022
Poland	LFS	2023
Republic of Moldova	LFS	2023
Romania	LFS	2022
Russian Federation	LFS	2023
Rwanda	LFS	2021
Samoa	LFS	2022
Sao Tome and Principe	MICS	2019
Senegal	EHCVM	2022
Serbia	NCLS	2021
Singapore	LFS	2023
Slovenia	LFS	2022
Somalia	LFS	2019
South Africa	QLFS	2023
Sri Lanka	LFS	2022
State of Palestine	MICS	2020
Switzerland	ESPA	2022
Thailand	LFS	2022
Timor-Leste	CENSUS	2022
Togo	ECVM	2019
Tonga	MICS	2019
Trinidad and Tobago	MICS	2022
Türkiye	LFS	2023
Uganda	LFS	2021
United Arab Emirates	LFS	2022
United Republic of Tanzania	LFS	2020
United States of America	CPS	2023
Uruguay	ECH	2023
Uzbekistan	MICS	2022
Vanuatu	MICS	2023

Country	Data source	Year
Viet Nam	MICS	2021
Yemen	MICS	2023
Zambia	LFS	2022
Zimbabwe	MICS	2019


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