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Intelligence System
DATA · MODELS · BETTER DECISIONS

Evidence-based health systems for a healthier, more prosperous Africa

Health Modelling

Data • Models • Better Health Outcomes

Integrated health data and modelling for stronger health systems and healthier communities

HEALTH MODELLING FOR A RESILIENT AFRICA

More Immunization	Lower Child Mortality	Stronger Health Systems	Reduced Inequalities	Healthier Communities

HLT 501 Health Sector Modelling

Course Technical Manual — EDIS Academy

Economic Development Intelligence System (EDIS)

Executive Summary

A health-sector model estate, and the judgement to say what each of its models does not establish

A health model is a claim about a population, a system or a plan. Each kind of claim rests on different evidence, and the three must never be mixed in one sentence.

This manual is the reference text for HLT 501. Part II is organised by health domain — one chapter per family of the model catalogue — because that is how a workplan is written. Parts III to V follow the health-system engine from demography to the handover. Chapter numbers are stable across versions.

Table 1: The course at a glance

COURSE CODE	HLT 501
COURSE	Health Sector Modelling
SCHOOL	05 Sector Planning — Health
DOCUMENT	Course Technical Manual
VERSION	2.0
BUILT	2026-08-24
LEARNING HOURS	55 (band 40–55)
MODEL ESTATE	EDIS Health Sector Decision Intelligence System (IntegratedHealthSystemModel v0.6.0) with the DHS population-health layer v1.0.0
POPULATION-HEALTH MODELS	97 cards in 14 domain families
SYSTEM MODELS	14 health-system modules, 10 optimisation models, 2 GIS modules, 4 integration links
EQUATION REGISTER	72 identifiers across 16 sections
SURVEY EVIDENCE	Uganda 2016 DHS (UG2016DHS); Kenya 2022 DHS (KE2022DHS)
SYSTEM-MODEL DEMO	Zandia (ZAN) — the health-system engine's SYNTHETIC demo country
GEOGRAPHIC DATA	20 sources across 55 African countries
AUDIENCE	Ministry of Health planners, health economists and statisticians; Ministry of Finance sector analysts
PREREQUISITES	EDIS 101; regression at the level of a logit; Julia at the level of reading a script

DATA AND SOURCING STATEMENT

Every number in this manual was produced by `_build/health_extract.py` from the implemented system at D:/EDIP/models/HealthModelling, and every figure by `_build/health_figures.py` from those same tables and from the geographic layers under `D:/EDIP/data`. Nothing is transcribed by hand.

Population-health estimates come from committed runs on Uganda 2016 DHS (UG2016DHS) and Kenya 2022 DHS (KE2022DHS) and are labelled with their survey. Health-system, optimisation and financing figures come from the engine's committed run on Zandia (ZAN) — the health-system engine's SYNTHETIC demo country and are labelled SYNTHETIC. Geographic figures come from real OpenStreetMap, geoBoundaries and WorldPop layers and are labelled with their source. No microdata, identifier or cluster coordinate appears anywhere in this course.

Contents

Preface — how to read this manual

A ministry of health asks three kinds of question, and they need three different kinds of model.

Table 2: Three questions, three model families, three kinds of evidence

The question	What answers it	Where in this manual
How many children are stunted, and which children?	A population-health model estimated from household survey microdata, with a design-based interval	Part II — Chapters 5 to 18
How many clinics, staff and medicines will that need, and what will it cost?	The health-system engine: demography, epidemiology, demand, capacity, workforce, supply chain and financing	Part III — Chapters 19 to 24
Where should the next ten facilities go, and who is still left out?	Geographic accessibility and the optimisation models, under declared external planning parameters	Part IV — Chapters 25 to 29

The three run on different data and carry different kinds of uncertainty. A population-health estimate rests on a real survey and carries a sampling interval. A system-model result rests on parameters someone chose and carries a sensitivity range. An optimisation result rests on an objective someone selected and is a different answer under a different objective. Mixing them in one sentence is the failure this manual is organised to prevent.

What this course is about, and what the survey is

THE SURVEY IS A DATA SOURCE, NOT THE SUBJECT

Demographic and Health Survey microdata is where most of the population-health models in Part II get their evidence. It is one input among several: the accessibility and optimisation models run on facility registers, population grids and road networks; the financing models run on budget and unit-cost tables; the epidemiology models run on incidence, case-fatality and vaccination parameters. Chapter 3 is the full inventory. Chapter 4 covers the estimation discipline a complex survey requires, because half the catalogue depends on it — but the course is about the health models, not about the survey.

What this manual covers

- Part I — the model estate, the data it runs on, and estimation under a complex survey design
- Part II — the 97 population-health model cards, one chapter per domain family A to N — what each estimates, how, what it produced, and what it feeds
- Part III — the health-system engine: demography, epidemiology and disease burden, service demand, facility capacity, workforce and supply chain

- Part IV — geographic accessibility, the four optimisation models, financing and costing, health outcomes and DALYs, and climate-health risk
- Part V — poverty and financial protection, the macro and CGE bridges, and the cross-sector handover
- Part VI — validation, worked numerical examples, case studies, policy interpretation, the laboratories and common errors
- Part VII — disclosure control, reproducibility and audit, and the review questions
- Appendices — glossary, the full catalogue, the equation register, notation, configuration, commands, answers, references, limitations, and every committed table

Conventions

Table 3: Typographic and labelling conventions

Convention	Meaning
`monospace`	A file, a function, a configuration key or a command, exactly as it appears in the system
H-x-nn	A stable equation identifier. The register holds 72 of them; Appendix C is the index
Card n	One of the 97 population-health model cards. Appendix B is the full catalogue
UG2016 / KE2022	A real estimate from a committed run of the Uganda 2016 or Kenya 2022 DHS
SYNTHETIC	A figure from the health-system engine's demo country. Structurally faithful; not evidence about any real country
HL-nn	A registered limitation. Appendix I lists all 12
§n	A section of the Academy master command

THE HABIT THIS COURSE IS TRYING TO BUILD

Before you report a number, say what kind of claim it is, what its uncertainty is, and what would change it. For a survey estimate that is the denominator, the interval and the disclosure status. For a system-model result it is the parameters and the sensitivity range. For an optimisation result it is the objective. Every laboratory ends by making you write those three things down, and the marking rubric weights honesty about limits at 20 per cent for the same reason.

The §7 Technical Manual Standard — where each requirement is met

§7 of the Academy command lists eighteen items every course technical manual must cover. This table is the index.

Table 4: §7 compliance index for HLT 501

§7 requirement	Where
Cover page, course code, version and intended audience	Cover
Course purpose, learning outcomes and prerequisites	Chapter 2
Conceptual and theoretical foundations	Chapters 1, 3; Part II opens each domain with its own
Mathematical model or analytical framework	Chapters 4, 19–31; the equation register, Appendix C
Definitions of sets, indices, variables and parameters	Chapter 19.1; Appendix D
Data sources, frequency, units, preprocessing and quality controls	Chapter 3; Appendix E
Calibration, estimation and assumptions	Chapter 4; Chapter 33.3; each domain chapter's assumptions table
EDIS implementation and model/API workflow	Chapters 1.4, 34
Scenario design	Chapters 23, 30.4, 31
Validation and diagnostics	Chapter 33
Worked numerical examples	Chapter 34
Case studies	Chapter 35; folder 10_Case_Studies
Policy interpretation	Chapter 36
Laboratory walkthroughs	Chapter 37; 04_Laboratory_Manual.docx
Common errors and troubleshooting	Chapter 38
Review questions	Chapter 41; Appendix H
Glossary	Appendix A
References and appendices	Appendix G; Appendices A–N

Part I — The model estate and its data

What the system models, where the numbers come from, and the estimation discipline a complex survey requires.

1. What this system models

The EDIS health estate is four things that share a configuration, a set of identifiers and a unit registry. This chapter is the map.

1.1 The four layers

Table 5: The estate, and what kind of evidence each layer carries

Layer	What it is	Scale	Evidence
Population health	97 model cards in 14 domain families, estimated from household survey microdata	97 Julia files under `src/Models/`	Real surveys, with design-based intervals
The health-system engine	Demography, epidemiology and disease burden, service demand, facility capacity, workforce, supply chain, financing and outcomes	14 modules under `src/Models/`	Parameterised; demonstrated on a synthetic country
Geography and optimisation	Accessibility measures and four mixed-integer or linear programmes solved with HiGHS	2 GIS modules and 10 optimisation modules	Real facility, boundary and population layers
Integration	Poverty microsimulation, macro and CGE exchange, the education link and the cross-sector transfer catalogue	4 modules under `src/Integration/`	File handover, one direction

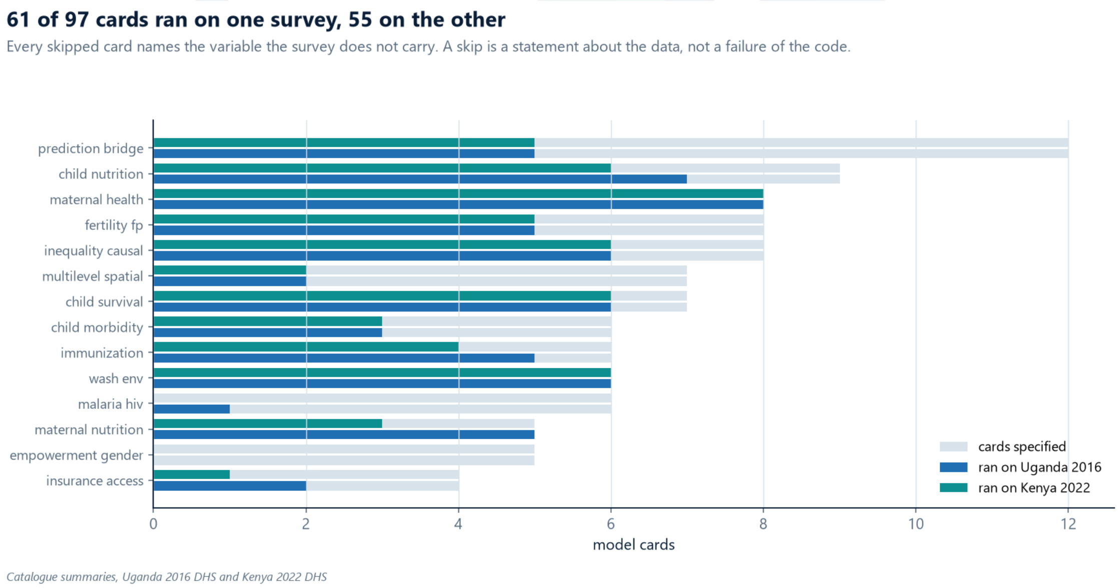
1.2 The fourteen population-health domains

Part II gives each of these a chapter. The completion columns are what the committed runs did with the family, not what the specification promises.

Table 6: The fourteen domains of Part II

	Domain	Cards	Uganda	Kenya	Chapter
A	Child Survival and Mortality	7	6	6	5
B	Maternal Health and Continuum of Care	8	8	8	6
C	Fertility, Family Planning and Reproductive Health	8	5	5	7
D	Child Nutrition and Growth	9	7	6	8
E	Maternal and Adult Nutrition and Anaemia	5	5	3	9
F	Child Morbidity and Treatment	6	3	3	10
G	Immunization and Preventive Child Health	6	5	4	11
H	Malaria, HIV and Biomarker Models	6	1	0	12
I	WASH, Household Environment and Environmental Health	6	6	6	13
J	Women's Empowerment, Gender and Violence-Related Health	5	0	0	14
K	Health Insurance, Access Barriers and Service Choice	4	2	1	15
L	Inequality, Decomposition and Causal Policy Analysis	8	6	6	16
M	Multilevel, Spatial and Small-Area Models	7	2	2	17
N	Prediction, Microsimulation and Bridge Models	12	5	5	18
	Total	97	61	55	—

Figure 1: Catalogue completion by family on two surveys



Notes: The catalogue is a contract; the survey decides how much of it is available. Source: Catalogue summaries, Uganda 2016 and Kenya 2022.

1.3 The health-system blocks

Each block owns a section of the equation register. Part III and Part IV work through them in the order the engine runs them.

Table 7: The 13 blocks of the health-system engine and where each is documented

Prefix	Block	Equations	Implemented in	Chapter
H-D	Demography	4	Models/Population.jl	19
H-E	Epidemiology and disease burden	10	Models/DiseaseBurden.jl	20
H-S	Service demand	3	extract_health_service_demand	21
H-C	Facility capacity, utilisation and queueing	5	Models/FacilityCapacity.jl	22
H-A	Geographic accessibility	8	GIS/Accessibility.jl	25
H-W	Health workforce	6	Models/WorkforcePlanning.jl	23
H-SC	Medicine supply chain	5	Models/SupplyChainModel.jl	24
H-F	Health financing, costing and value	6	Models/HealthFinancing.jl	27
H-O	Health outcomes — GBD DALYs	4	extract_health_outcomes	28
H-OPT	Optimisation	4	Optimization/*.jl	26
H-P	Poverty, welfare and financial protection	8	Integration/Poverty.jl	30
H-CL	Climate-health risk	5	GIS/ClimateRisk.jl	29
H-M	Macro, CGE and education integration	4	Integration/{MacroLink,CDCGELink, EducationLink}.jl	31

1.4 How a run flows

A country run is a sequence, and every stage feeds the next. The point of the sequence is that a facility plan at the end is a function of a demography estimate at the beginning — so an error in the age structure is an error in the procurement bill.

- Demography — cohort-component projection from the base-year age structure (H-D-01 to H-D-04)
- Epidemiology — cases and prevalence per area, disease and year, with climate and prevention multipliers (H-E-03 to H-E-05)
- Service demand — need from cases through visits-per-case, then demand through care-seeking, coverage and price (H-S-01 to H-S-03)
- Capacity and utilisation — effective capacity from staffing, readiness and hours; served, unmet and the waiting probability (H-C-01 to H-C-05)
- Workforce and supply — WISN requirement, stock-flow projection, commodity requirement and the (s,S) inventory policy (H-W, H-SC)
- Accessibility — travel time, threshold coverage, floating catchments and the underserved gap score (H-A-01 to H-A-08)
- Optimisation — facility siting, workforce allocation, referral flow and supply distribution (H-OPT-01 to H-OPT-04)
- Financing and outcomes — cost, envelope, gap, cost-effectiveness, deaths and DALYs (H-F, H-O)

- Distribution and handover — poverty and financial protection, then the cross-sector transfer files (H-P, H-M)

1.5 What the committed runs produced

Table 8: Headline results from the two committed runs

Quantity	Value	Which run
Population-health cards completed	61 of 97	Uganda 2016 DHS (UG2016DHS)
Cards completed on a second survey	55 of 97	Kenya 2022 DHS (KE2022DHS)
Validation checks	241 of 242 pass	Uganda 2016 DHS (UG2016DHS)
National population	2,470,000	Zandia (ZAN) — the health-system engine's SYNTHETIC demo country
Total service demand	1,041,366 contacts/year	Zandia (ZAN) — the health-system engine's SYNTHETIC demo country
Unmet demand	92,987 contacts/year	Zandia (ZAN) — the health-system engine's SYNTHETIC demo country
Workforce gap	36.5 FTE	Zandia (ZAN) — the health-system engine's SYNTHETIC demo country
Required expenditure	$59.4M	Zandia (ZAN) — the health-system engine's SYNTHETIC demo country
Deaths and DALYs	13,189 deaths, 763,634 DALYs per year	Zandia (ZAN) — the health-system engine's SYNTHETIC demo country
Catastrophic health spending	35.2 %	Zandia (ZAN) — the health-system engine's SYNTHETIC demo country

Notes: The first three rows are real; the rest are SYNTHETIC.

WHY THE LABELS MATTER (HL-02)

The population-health layer has been run on real surveys and its estimates are evidence about Uganda and Kenya. The health-system engine has been run end to end, but on a synthetic demo country: its population, facilities, workforce, financing and disease parameters are demo values. Both are useful — the first as evidence, the second as a demonstration that the mechanics work and as a template for a real country. Presenting a synthetic figure as evidence about a real health system is on this course's automatic-fail list.

2. Purpose, learning outcomes and prerequisites

2.1 Purpose

HLT 501 trains an analyst to work across the whole EDIS health estate: to estimate a population-health indicator from survey microdata and report it defensibly; to run the health-system engine from demography through to financing and say which of its numbers are parameters and which are results; to build an accessibility surface and an optimised facility plan and state the objective that produced it; and to hand the whole thing to a poverty, macro or CGE model without manufacturing a value the data cannot support.

It is a sector-planning course, not a statistics course and not an epidemiology course. The mathematics is here because a planner who cannot say why effective capacity differs from nominal capacity will plan against a register, and because the difference between an odds ratio and a risk ratio has moved budgets. Every equation is one the implemented system computes and carries its identifier from the register.

2.2 Learning outcomes

- Locate any model in the estate: name its family or block, its equation identifiers, its implementing module and its evidence base.
- Produce a design-based population-health estimate with its interval, denominator, design effect and disclosure status, and reproduce it in a second implementation.
- Read and report any of the estimator families the catalogue uses — binary, discrete-time survival, ordinal, count, multinomial, continuation-ratio, quantile and multilevel — on the correct scale.
- Work through a domain family end to end: what each card estimates, which ran, what the survey refused, and what the family feeds downstream.
- Project a population by cohort component and explain why the age structure, not the total, drives service need.
- Run the epidemiology engine, distinguish the endemic path from the compartmental models, and compute a reproduction number and a population attributable fraction.
- Convert cases into service need and need into demand, and state which of the three a reported number is.
- Compute effective capacity, utilisation, unmet demand and the waiting probability, and explain the gap from nominal capacity.
- Produce a WISN workforce requirement and a stock-flow projection, and a commodity requirement under an (s,S) inventory policy.
- Build accessibility measures from travel time through to two-stage floating catchments, and defend the measure chosen.
- Formulate and read a facility-planning optimisation, and report how the recommendation changes with the objective and the budget.
- Cost a health system bottom-up, compute the financing gap and fiscal space, and produce an ICER with a WHO-CHOICE verdict.

- Compute DALYs from deaths and cases, and say which reference parameters the result rests on.
- Apply the climate-health response functions within their support, and the poverty and financial-protection measures across the distribution.
- Produce cross-sector transfer files with their declared refusals, and write a handover a receiving modeller can act on.

2.3 Prerequisites

Table 9: Prerequisites for HLT 501

Requirement	Level	Why
EDIS 101	Required	The platform vocabulary — scenario, run identifier, transfer file, unit registry — is assumed throughout
Regression at the level of a logistic model	Required	Part II extends it; it does not introduce it
Julia — reading and modifying a script	Required	Every laboratory runs Julia. No package authoring is needed
Linear programming at the level of reading a formulation	Useful	Chapter 26 states four programmes; it does not teach the simplex method
Household survey experience (DAT 703 or equivalent)	Useful	Chapter 4 revises weights and clustering compactly
GIS at the level of a choropleth	Useful	Chapter 25 explains the measures; the laboratories supply the layers
R	Optional	Used only for the cross-check in Laboratory 02

2.4 What this course does not claim

- It does not give access to microdata — Restricted survey files stay where the national statistical office puts them. Every laboratory runs on committed outputs and on shipped geographic layers.
- It does not produce a validated country health plan — The health-system engine has been run end to end on a synthetic country. Producing a real one requires national census, facility, workforce, surveillance, financing and household data (HL-02).
- It does not calibrate an epidemic — The compartmental models are implemented and tested but not calibrated to the demo diseases; the endemic engine is the production path (HL-03).
- It does not deliver a health-macro equilibrium — The CGE link is a one-directional file handover with no iteration to convergence (HL-09).
- It does not validate against published national figures — Two implementations of one definition agreeing is not agreement with a national report (HL-11).

3. The data the estate runs on

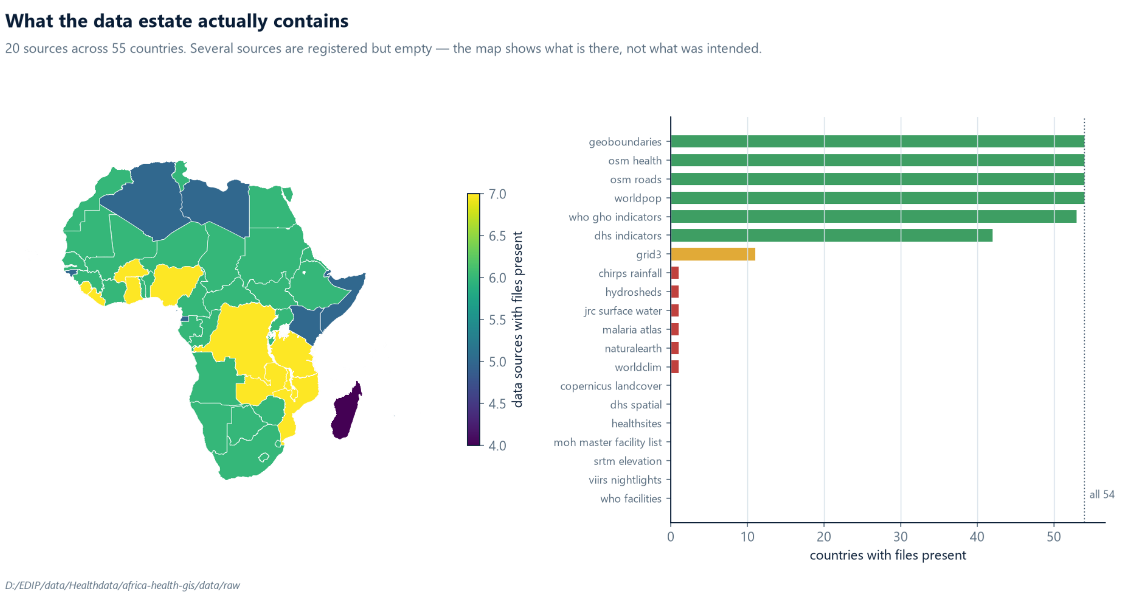
Different layers of the estate run on different data, and the commonest planning error is to assume that one source can answer a question that belongs to another. A household survey does not know where the clinics are; a facility register does not know who is ill; a population grid knows neither.

3.1 The inventory

Table 10: What each layer of the estate runs on, and what is actually present

Data	What it supports	Where it comes from	Status
Household survey microdata (DHS recodes)	The whole of Part II — prevalence, determinants, inequality, small-area estimation	National statistical offices, under restriction	Committed run outputs shipped; microdata never
Facility registers	Accessibility, capacity, optimisation (Chapters 22, 25, 26)	OpenStreetMap, WHO, ministry master lists	OSM present for 54 countries; WHO and ministry lists mostly placeholders
Administrative boundaries	Every map, every area-level estimate, every concordance	geoBoundaries ADM0 to ADM5	present for 54 countries
Population grids	Demand origins, catchment populations, coverage denominators	WorldPop UN-adjusted	present for 54 countries
Road networks	Travel time and the referral network	OpenStreetMap / Geofabrik	present for 54 countries; routing itself is partial (HL-04)
Climate layers	The climate multiplier and the climate-health chapter	CHIRPS rainfall, WorldClim, Malaria Atlas	sparse — a handful of countries
Aggregate indicators	Benchmarking and the reference tables	WHO Global Health Observatory, DHS StatCompiler	DHS indicators present for 42 countries
Planning parameters	Unit costs, salaries, capacity per facility, budgets, elasticities	Ministry budget books, procurement data, the unit-cost tables	Configuration, not data — Chapter 27

Figure 2: What the health GIS estate actually holds



Notes: the number of data sources with real files, country by country. Source: D:/EDIP/data/Healthdata/africa-health-gis.

REGISTERED IS NOT PRESENT (HL-12)

The health GIS estate registers 20 sources across 55 countries. Several of them — the WHO facility list, the DHS spatial layers, Healthsites, the GHO indicator pulls and Copernicus land cover — hold a file called `HOW_TO_SUPPLY_THIS_DATASET.md` for most countries rather than data. The map above counts files that are actually there. Read it before planning an analysis that depends on one of them.

3.2 The units and the provenance tag

Every quantity in the estate carries a unit from the unit registry and a provenance tag. The tag is the part that travels into a report.

Table 11: Provenance tags, from the unit registry

Tag	Meaning
observed	measured or reported directly in a source
estimated	the output of a model fitted to observed data
imputed	filled by a documented imputation rule
projected	carried forward by a projection model
scenario	the result of a counterfactual lever setting
synthetic	generated for demonstration or testing

Notes: The system never fabricates a value: a quantity with no tag is a bug.

Table 12: The unit registry

Quantity	Unit
Population	persons
Incidence	cases per 1,000 person-years
Service demand	contacts per year
Travel time	minutes
Distance	kilometres
Workforce	full-time equivalents
Cost	USD, constant base-year
Capacity	beds; contacts per year
Medicines	medicine units
Burden	DALYs
Shares and rates	fraction in [0,1]

3.3 The survey recodes, and which weight applies

Part II depends on choosing the right file. The recode determines the population, and it determines the weight.

Table 13: Core survey files and analytical units, from the population-health specification

DHS file	Typical unit	Examples of variables	Main model uses
HR/PR	Household/member	wealth, WASH, residence, household composition	poverty, WASH, insurance, vulnerability
IR	Women 15–49	fertility, ANC, delivery, contraception, empowerment	maternal health, fertility, reproductive health
MR	Men	fertility preferences, HIV knowledge/testing, demographics	gender/reproductive-health models
BR/KR	Births/children	birth history, mortality, immunization, illness, nutrition	child survival, vaccination, morbidity
AR/CR	Biomarkers/children	anaemia, malaria, HIV/anthropometry where available	disease and nutrition models
GPS	Survey cluster	displaced coordinates	spatial exposure, accessibility, small-area modelling

Table 14: The recode traps

Recode	Unit	The trap
HR	Household	—
PR	Household member	uses the **household** weight `hv005`, not `v005`
IR	Woman 15–49	antenatal and delivery questions refer to the **most recent** birth
BR	Birth, including deaths	the **only** correct source for mortality
KR	Living child under five	survivor selection — it is **not** a mortality file
MR / CR	Man / couple	a subsample, with a different weight
GE	Cluster	coordinates are **displaced**, and are never published

3.4 Displacement, and what it means for every map

Survey cluster coordinates are displaced before release: 2 km for urban clusters, 5 km for rural, and 10 km for a randomly selected one per cent of rural clusters. Displacement is a disclosure control, not measurement noise.

Table 15: The displacement rules, enforced by `GIS/Accessibility.jl` and `assert_safe_output`

Operation	Correct	Incorrect
Extract a raster covariate	Zonal statistic over a buffer at least as large as the displacement radius	Point extraction at the released coordinate
Assign a cluster to a district	The survey's own region or district variable	Spatial join on the displaced point
Compute distance to a facility	The distribution over the buffer, or displacement stated as measurement error	A single distance reported as a fact
Publish a map	An areal surface with uncertainty and a privacy note	Anything showing cluster locations

THE FACILITY MAPS IN THIS COURSE ARE NOT SURVEY MAPS

Chapters 25 and 26 map facility registers, boundaries and population grids — none of which is displaced, and none of which carries a respondent. That is why the facility maps in this manual can show points and the survey maps cannot. Keeping the two straight is the whole of the governance chapter.

3.5 Configuration is not code

Everything country-, survey- or policy-specific lives in YAML. The population-health layer ships 97 model configurations and 13 configuration files; the health-system engine takes its parameters from the same place. A variable name never appears in a source file.

Table 16: The configuration surface

File	Governs
`project.yml`	toolchain, pilot, analysis defaults, restricted-module switches
`countries.yml`	ISO3, survey names, admin labels, comparability breaks
`surveys.yml`	eligibility, required recodes per family, pooling rules
`variables.yml`	the variable map with fallbacks and decode rules
`outcomes.yml`	the indicator dictionary — numerator, denominator, exclusions, source variables
`covariates.yml`	covariate sets, derivations and **causal roles**
`model_registry.yml`	33 production entries, one per model
`disclosure_control.yml`	thresholds, suppression rules, identifier blocklist
`scenario_definitions.yml`	lever grammar, external assumptions, accounting identities
`cross_sector_links.yml`	export schemas and explicit refusals
`config/health/model.yml`	the health-system engine's parameters: capacities, unit costs, elasticities, disease table

4. Estimation under a complex survey design

Roughly half the catalogue is estimated from a stratified two-stage cluster sample, and every one of those estimates is wrong in a predictable way if the design is ignored. This chapter is the compact treatment: enough to read and defend a Part II estimate, and no more.

4.1 The design

Strata are region crossed with urban/rural. Clusters — the primary sampling units — are drawn with probability proportional to size, and households are drawn systematically within them.

SAMPLE WEIGHT

```
w_i = v005_i / 10^6 women, births, children
w_i = hv005_i / 10^6 households and members
```
the weight follows the recode file, not the question; the division by 10^6 happens once (1)

SAMPLE SCALE, NOT POPULATION SCALE

Survey weights normalise to the sample. A weighted total is on the sample scale unless it has been explicitly rescaled to an external population, and the system labels which of the two it is

> returning. Multiplying a weighted proportion by a national population is a raking operation with assumptions — Chapter 30.5 covers the calibration that makes it legitimate.

4.2 Point estimation and variance

EQ. RATIO ESTIMATOR

$$\hat{R} = \Sigma\_i\ w\_i\ y\_i\ /\ \Sigma\_i\ w\_i \tag{2}$$

EQ. TAYLOR-LINEARISED VARIANCE

$$\begin{aligned}
&u_i = w_i\ (y_i - \hat{R})\\
&u_hj = \Sigma_\{i \in hj\}\ u_i\\
&\mathrm{Var}(\hat{R}) = (1/W^2)\ \Sigma_h\ [\ m_h/(m_h-1)\ ]\ \Sigma_\{j=1..m_h\}\ (u_hj - \bar{u}_h)^2\\
&m_h \text{ is the number of PSUs in stratum } h;\ W = \Sigma_i\ w_i
\end{aligned} \tag{3}$$

Read the structure rather than the algebra. The outer sum runs over strata; the inner sum over clusters within a stratum; and what varies is the cluster total, not the individual record. Two children in the same village are not two independent observations of a national rate.

4.3 The design effect

EQ. DESIGN EFFECT

$$\begin{aligned}
&\mathrm{deff} = \mathrm{Var_design}(\hat{\theta})\ /\ [\ \hat{p}(1 - \hat{p})\ /\ n\ ]\\
&n_eff = n\ /\ \mathrm{deff}\\
&\text{interval width} \approx \sqrt{\mathrm{deff}} \times \text{naive}
\end{aligned} \tag{4}$$

Figure 3: Design effect and effective sample size

Notes: Clustering means a survey of several thousand records carries the information of a much smaller simple random sample. Source: Uganda 2016 DHS · committed run.

Design effects are not transferable. Borrowing one from another indicator, domain or round is a guess; the system computes it per cell, which costs nothing.

4.4 Domains, and the subpopulation rule

Table 17: Why the subpopulation rule exists

Approach	Point estimate	Variance
Subset the data and re-run	correct	**wrong** — strata and PSUs are lost with the deleted records
Keep all records, zero the outside contributions	correct	correct

4.5 Regression under the design

EQ. DESIGN-BASED SANDWICH

$$\hat{V}(\hat{\beta}) = I^{-1} [\Sigma\_h m\_h/(m\_h-1) \Sigma\_j s\_hj s\_hj'] I^{-1}$$

$$s\_hj = \Sigma\_\{i \in hj\} w\_i (y\_i - \hat{\mu}\_i) x\_i$$

score contributions aggregated to the PSU before being squared - the same structure as the ratio-estimator variance (5)

EQ. AVERAGE MARGINAL EFFECT

$$AME\_k = (1/n) \Sigma\_i \hat{\mu}\_i (1 - \hat{\mu}\_i) \hat{\beta}\_k$$

computed for every logit and written beside the coefficients (6)

WHY AN ODDS RATIO IS NEVER PUBLISHED ALONE

An odds ratio of 1.5 means very different things at 5 per cent and at 50 per cent prevalence, and a policy audience will read it as a risk ratio. Chapter 34.2 does the arithmetic on a real coefficient; Case Study 03 follows the consequence through four documents to a cabinet memo.

4.6 Comparison, and the two non-statistical conditions

EQ. RAO–SCOTT FIRST-ORDER CORRECTION

$$X^2\_RS = X^2 / mean(deff)$$

both statistics are reported, so the size of the correction is visible (7)

- Definition stability — `surveys.yml` records comparability breaks and `outcomes.yml` marks each indicator comparable or not. A trend across a break is refused.
- Overlapping domains — boundaries change. A district created between two rounds cannot be trended without a concordance, and the system requires one rather than matching on name.

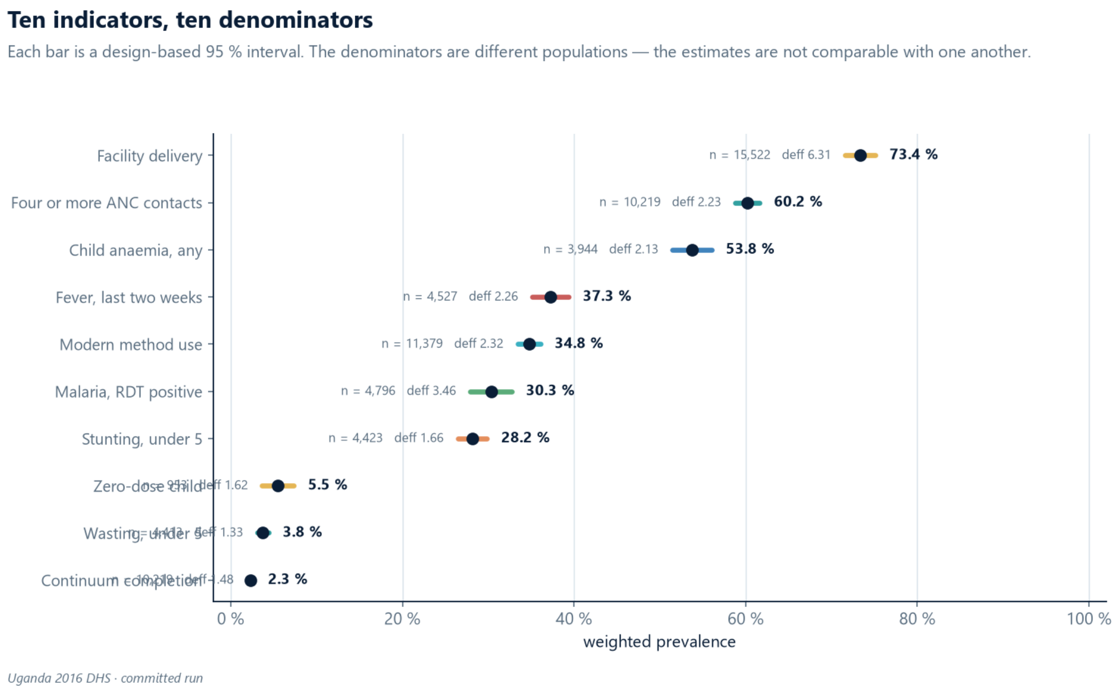
4.7 What a published cell carries

Table 18: National stunting, Uganda 2016 DHS (UG2016DHS)

Field	Pilot value	Why it is not optional
estimate	28.2 %	the point estimate alone invites false precision
design-based interval	95 % CI 26.5–29.9	computed from the actual cluster and stratum structure
unweighted denominator	4,423	disclosure control acts on the unweighted count
design effect	1.66	ignoring it understates the interval by roughly its square root

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

Figure 4: National health indicators with design-based 95 per cent intervals



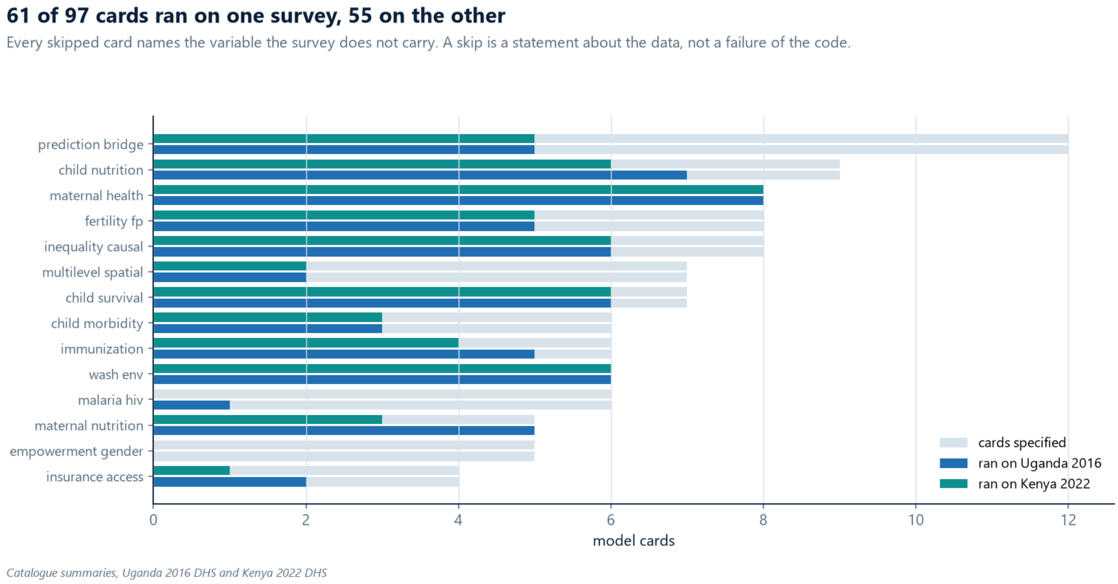
Notes: The interval is computed from the survey's own cluster and stratum structure, not from a simple-random-sample formula. Source: Uganda 2016 DHS · committed run.

> **Part II — The population-health domains**
>
> One chapter for each of the 14 families of the model catalogue. Every one of the 97 cards is covered.

Each chapter has the same seven sections. Section 1 says what the family estimates and why a ministry asks for it. Section 2 states the trap — the one mistake that family invites. Section 3 covers every card in the family: outcome, specification, inputs, estimator. Section 4 gives the survey-design treatment and the diagnostics the cards must carry. Section 5 reports what the committed runs produced. Section 6 records what the surveys refused, verbatim. Section 7 names where the family goes downstream.

The catalogue is a contract, not a menu: what runs depends on what the survey contains, and the difference between the two surveys is itself information.

Figure 5: Catalogue completion by family on two surveys



Notes: The catalogue is a contract; the survey decides how much of it is available. Source: Catalogue summaries, Uganda 2016 and Kenya 2022.

5. A. Child Survival and Mortality

Table 19: Child Survival and Mortality: the family at a glance

Cards in the family	**7**
Completed on Uganda 2016 DHS (UG2016DHS)	6
Completed on Kenya 2022 DHS (KE2022DHS)	6
Implemented in	`src/Models/child_survival/` — 7 Julia files
Downstream	Demography (H-D-02), disease burden, child-survival scenarios and health-investment targeting.

5.1 What this family estimates

Neonatal, post-neonatal, infant and under-five death; competing risks; the birth-interval and high-risk-fertility pathways.

Child mortality is the indicator against which health systems are judged internationally, and it is the one a household survey measures best — because the birth history records deaths that no registration system in most of the region captures. It is also the family where the file choice is not negotiable.

5.2 The trap

FAMILY A

Mortality comes from the birth history. The children's file holds survivors, so estimating mortality from it conditions on the outcome — and the resulting bias is downward and unbounded.

5.3 The models

All 7 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 20: Family A: the 7 model cards

#	Model	Outcome	Estimator	Ran	n
1	Neonatal mortality probability	death within 0–27 days	survey-weighted logit/probit; multi-level extension	yes	11,667
2	Post-neonatal mortality	death 1–11 months	survey-weighted logit	yes	50,555
3	Infant mortality survival	time to death before age 1	Cox or discrete-time hazard	yes	39,701
4	Under-five mortality survival	time to death before age 5	Cox/Weibull/discrete-time hazard	yes	615
5	Competing-risk child mortality	cause/state-specific child exit where cause data exist	cause-specific/Fine-Gray where defensible	no	—
6	Birth-interval mortality model	effect of preceding interval on mortality	survey logit with nonlinear interval terms	yes	32,027
7	High-risk fertility mortality model	joint demographic risk score and mortality	survey logit	yes	32,027

5.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 21: Specification and inputs

#	Model	Core specification	Key inputs
1	Neonatal mortality probability	Pr(ND_i=1)=F(X_iβ)	maternal age, birth order, birth interval, birth size, ANC, delivery place, wealth, WASH, residence
2	Post-neonatal mortality	Pr(PND_i=1)=F(X_iβ)	breastfeeding proxies, vaccination, WASH, wealth, maternal education, residence
3	Infant mortality survival	h_i(t)=h_0(t)exp(X_iβ)	birth history, maternal/household covariates
4	Under-five mortality survival	h_i(t)=h_0(t)exp(X_iβ)	birth characteristics, household environment, maternal factors
5	Competing-risk child mortality	h_{ik}(t)=h_{0k}(t)exp(X_iβ_k)	verbal/cause proxies where available plus DHS covariates
6	Birth-interval mortality model	Pr(Death_i=1)=F(β_1Interval_i+X_iγ)	preceding birth interval, parity, maternal age
7	High-risk fertility mortality model	Pr(Death_i=1)=F(Risk_iβ+X_iγ)	young/older mother, high parity, short interval

5.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 22: What each card must report before its output is usable

#	Model	Diagnostics and validation
1	Neonatal mortality probability	weighted calibration, ROC/AUC, rare-event sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
2	Post-neonatal mortality	calibration, influential observations, subgroup validation. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
3	Infant mortality survival	PH test, censoring checks, survival calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
4	Under-five mortality survival	PH and functional-form tests. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
5	Competing-risk child mortality	competing-risk calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
6	Birth-interval mortality model	functional-form and parity sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
7	High-risk fertility mortality model	risk-definition sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

5.5 What the committed runs produced

Table 23: Design-based indicators, Uganda 2016 DHS (UG2016DHS)

Indicator	Estimate	95 % CI	n	deff
Under-five survival	1.3 %	1.3–1.4	143,471	1.94

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

Mortality rates from the birth history

Table 24: Mortality, Uganda 2016 DHS (UG2016DHS)

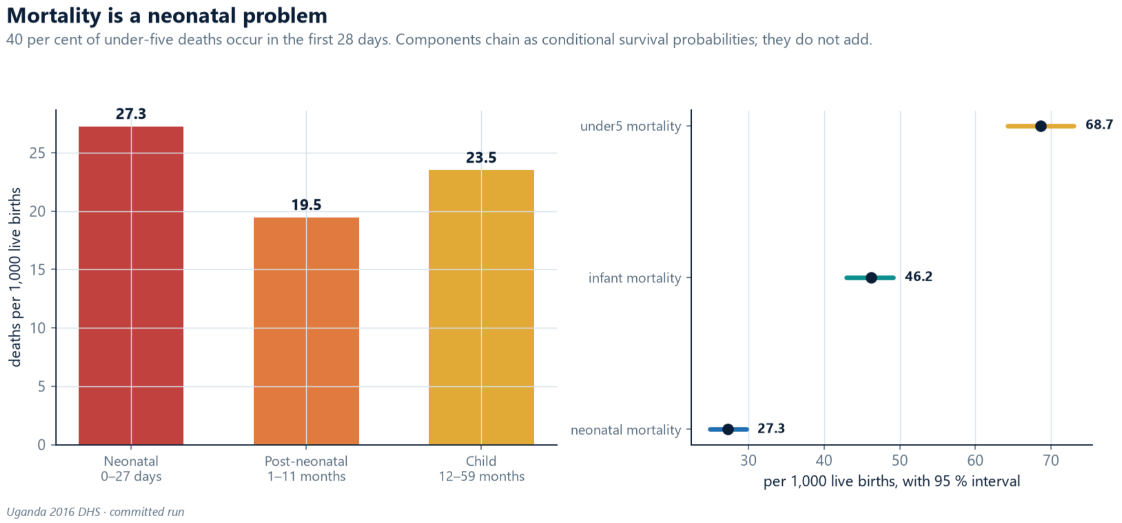
Indicator	Per 1,000 live births	95 % CI	Births in the window
neonatal mortality	27.3	24.9–29.7	143,471
infant mortality	46.2	42.9–49.2	143,471
under5 mortality	68.7	64.3–73.0	143,471

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

THE FOUR BIASES, AND THEIR DIRECTION (HL-10)

Recall error — downward. Age heaping on twelve months — ambiguous, because it moves deaths across the infant boundary. Omission of early deaths — downward. Selection on maternal survival, because children of women who themselves died are not observed — downward. Three of the four run the same way, and the registry entry states all four. A rate quoted without them fails this course's assessment.

Figure 6: Under-five mortality decomposed into its age components



Notes: Risk is concentrated in the neonatal period, which is invisible in the headline rate. Source: Uganda 2016 DHS · committed run.

under5 survival coef

Discrete-time hazard, under-five survival. The link is complementary log-log, so exp(β) is a hazard ratio and not an odds ratio; interval 1, the neonatal interval, is the reference.

Table 25: under5 survival coef, Uganda 2016 DHS (UG2016DHS)

term	estimate	se	z	p
(Intercept)	-4.2910	0.2282	-18.8051	0.0000
interval_c: 2	-0.3396	0.0644	-5.2742	0.0000
interval_c: 3	-0.9532	0.0855	-11.1443	0.0000
interval_c: 4	-1.3820	0.1072	-12.8958	0.0000
interval_c: 5	-1.9303	0.1361	-14.1809	0.0000
interval_c: 6	-2.5820	0.1832	-14.0966	0.0000
wealth_c: 2	-0.0758	0.0806	-0.9402	0.3471
wealth_c: 3	-0.1449	0.0842	-1.7209	0.0853
wealth_c: 4	-0.0857	0.0888	-0.9650	0.3345
wealth_c: 5	-0.2145	0.1264	-1.6967	0.0897
edu_c: none	1.1204	0.2258	4.9620	0.0000
edu_c: primary	0.8356	0.2187	3.8215	0.0001
edu_c: secondary	0.4832	0.2181	2.2151	0.0268
res_c: urban	0.0162	0.1026	0.1582	0.8743

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

5.6 What the surveys refused

Table 26: Verbatim, from the catalogue summaries

#	Model	Survey	Reason the run gave
5	Competing-risk child mortality	Uganda 2016 DHS, Kenya 2022 DHS	required DHS variable(s) ["b_cause_of_death"] absent from the BR recode; no substitute used

5.7 Where this family goes

Demography (H-D-02), disease burden, child-survival scenarios and health-investment targeting.

Table 27: Each card's declared integration target

#	Model	Integration target
1	Neonatal mortality probability	feeds child-survival scenarios and health-investment targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
2	Post-neonatal mortality	links WASH, nutrition and preventive-health interventions. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
3	Infant mortality survival	parameterizes infant survival in demographic simulations. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
4	Under-five mortality survival	core health-outcome layer for EDIS. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
5	Competing-risk child mortality	supports targeted intervention portfolios. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
6	Birth-interval mortality model	links family planning to survival benefits. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
7	High-risk fertility mortality model	family-planning policy targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

5.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

THE RULE THAT APPLIES TO EVERY CARD IN PART II

Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

6. B. Maternal Health and Continuum of Care

Table 28: Maternal Health and Continuum of Care: the family at a glance

Cards in the family	**8**
Completed on Uganda 2016 DHS (UG2016DHS)	8
Completed on Kenya 2022 DHS (KE2022DHS)	8
Implemented in	`src/Models/maternal_health/` — 8 Julia files
Downstream	Service demand for MATERNAL and DELIVERY (H-S-01), facility and workforce planning.

6.1 What this family estimates

Antenatal adequacy and timing, contact counts, skilled attendance, facility and caesarean delivery, postnatal care, and completion of the continuum.

The continuum of care is a sequence, and a ministry's question is almost never how many women complete it. It is where they are lost, because that is where a programme intervenes. This family supplies both the levels and the transitions.

6.2 The trap

FAMILY B

Four cards in this family count four different populations. Comparing across them compares denominators, not care.

6.3 The models

All 8 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 29: Family B: the 8 model cards

#	Model	Outcome	Estimator	Ran	n
8	Adequate ANC model	probability of adequate antenatal contacts	survey logit/probit	yes	10,219
9	Early ANC initiation	first ANC in first trimester	survey logit	yes	10,019
10	Number of ANC contacts	ANC visit count	Poisson/negative binomial	yes	10,219
11	Skilled birth attendance	skilled attendant at delivery	survey logit/multilevel logit	yes	15,522
12	Facility delivery	delivery in health facility	survey logit	yes	15,522
13	Caesarean delivery	C-section probability	survey logit	yes	15,460
14	Postnatal care	timely postnatal check	survey logit	yes	10,219
15	Maternal continuum completion	ANC→facility/SBA→PNC completion	ordered/multinomial model	yes	10,219

6.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 30: Specification and inputs

#	Model	Core specification	Key inputs
8	Adequate ANC model	Pr(ANC_i=1)=F(X_iβ)	age, parity, education, wealth, residence, autonomy, media exposure
9	Early ANC initiation	Pr(Early_i=1)=F(X_iβ)	pregnancy order, education, wealth, residence
10	Number of ANC contacts	E(ANC_i|X_i)=exp(X_iβ)	maternal and household covariates
11	Skilled birth attendance	Pr(SBA_i=1)=F(X_iβ)	education, wealth, parity, ANC, residence, autonomy
12	Facility delivery	Pr(Facility_i=1)=F(X_iβ)	wealth, residence, ANC, birth order, perceived access barriers
13	Caesarean delivery	Pr(CS_i=1)=F(X_iβ)	maternal age, parity, wealth, residence, facility delivery
14	Postnatal care	Pr(PNC_i=1)=F(X_iβ)	delivery mode/place, ANC, education, wealth
15	Maternal continuum completion	Pr(COC_i=k)=exp(X_iβ_k)/Σ_j exp(X_iβ_j)	maternal and access variables

6.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 31: What each card must report before its output is usable

#	Model	Diagnostics and validation
8	Adequate ANC model	weighted calibration, specification tests. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
9	Early ANC initiation	recall-window sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
10	Number of ANC contacts	overdispersion, zero counts. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
11	Skilled birth attendance	cluster heterogeneity, calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
12	Facility delivery	classification sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
13	Caesarean delivery	rare-event/subgroup calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
14	Postnatal care	timing-definition sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
15	Maternal continuum completion	category calibration, IIA if multinomial. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

6.5 What the committed runs produced

Table 32: Design-based indicators, Uganda 2016 DHS (UG2016DHS)

Indicator	Estimate	95 % CI	n	deff
Four or more antenatal contacts	60.2 %	58.8–61.6	10,219	2.23
Facility delivery	73.4 %	71.6–75.1	15,522	6.31
Continuum completion	2.3 %	2.0–2.7	10,219	1.48

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

The cascade, transition by transition

Table 33: Maternal cascade transitions, Uganda 2016 DHS (UG2016DHS)

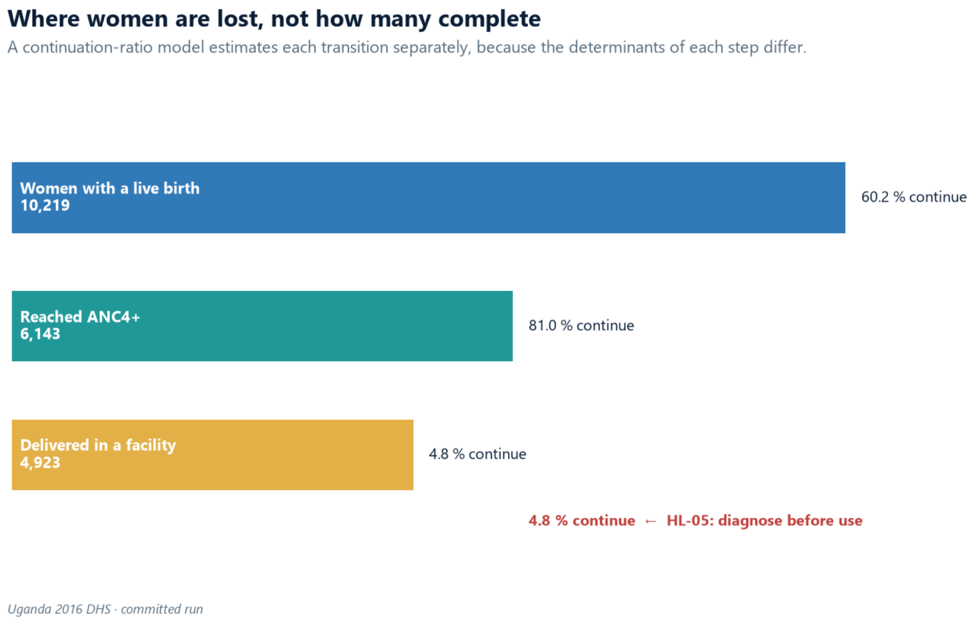
Transition	At risk	Continued	Dropped
no ANC4+ -> ANC4+	10,219	60.2 %	39.8 %
ANC4+ -> facility delivery	6,143	81.0 %	19.0 %
facility delivery -> postnatal check	4,923	4.8 %	95.2 %

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

HL-06 — A NUMBER TO DIAGNOSE, NOT TO REPORT

The third transition reports a continuation of 4.8 %. Taken at face value that is a near-total collapse of postnatal care, which would be the most important finding in the run. It is far more likely to be a universe or definition problem: the postnatal-check question has a short recall window, a specific timing condition, and a different eligible subset from the delivery question. Chapter 38.5 works the diagnosis through in six steps.

Figure 7: The maternal continuum of care as a funnel



Notes: The third transition is registered as HL-05: it must be diagnosed before it is used. Source: Uganda 2016 DHS · committed run.

anc4 coef

Survey logit, four or more antenatal contacts.

Table 34: anc4 coef, Uganda 2016 DHS (UG2016DHS)

term	estimate	se	z	p	odds ratio	or low	or high
(Intercept)	1.0690	0.1545	6.9188	0.0000	2.9124	2.1515	3.9425
wealth_c: 2	0.1184	0.0796	1.4867	0.1371	1.1257	0.9630	1.3158
wealth_c: 3	0.1857	0.0907	2.0485	0.0405	1.2041	1.0081	1.4382
wealth_c: 4	0.2794	0.0909	3.0736	0.0021	1.3224	1.1065	1.5803
wealth_c: 5	0.2938	0.1071	2.7427	0.0061	1.3415	1.0874	1.6548
edu_c: none	-0.6376	0.1342	-4.7496	0.0000	0.5286	0.4063	0.6877
edu_c: primary	-0.5792	0.1138	-5.0873	0.0000	0.5604	0.4483	0.7005
edu_c: secondary	-0.3742	0.1206	-3.1040	0.0019	0.6878	0.5431	0.8712
res_c: urban	0.1044	0.0876	1.1915	0.2335	1.1101	0.9349	1.3181
maternal_age	-0.0121	0.0035	-3.4287	0.0006	0.9880	0.9812	0.9948

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

facility delivery coef

Survey logit, facility delivery.

Table 35: facility delivery coef, Uganda 2016 DHS (UG2016DHS)

term	estimate	se	z	p	odds ratio	or low	or high
(Intercept)	2.2150	0.2949	7.5101	0.0000	9.1612	5.1392	16.3306
wealth_c: 2	-0.1193	0.0791	-1.5080	0.1315	0.8875	0.7600	1.0364
wealth_c: 3	0.1740	0.0982	1.7725	0.0763	1.1900	0.9818	1.4425
wealth_c: 4	0.4463	0.1080	4.1305	0.0000	1.5625	1.2643	1.9310
wealth_c: 5	1.1693	0.1447	8.0811	0.0000	3.2197	2.4246	4.2754
edu_c: none	-1.8865	0.2943	-6.4101	0.0000	0.1516	0.0851	0.2699
edu_c: primary	-1.6488	0.2860	-5.7657	0.0000	0.1923	0.1098	0.3368
edu_c: secondary	-0.8851	0.2892	-3.0609	0.0022	0.4127	0.2341	0.7274
res_c: urban	0.3847	0.1285	2.9951	0.0027	1.4692	1.1422	1.8899

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

cascade coef

Continuation-ratio model: one set of coefficients per transition, because the determinants of each step differ.

Table 36: cascade coef, Uganda 2016 DHS (UG2016DHS)

transition	term	estimate	se	odds ratio	or low	or high
no ANC4+ -> ANC4+	(Intercept)	0.0280	0.0717	1.0284	0.8935	1.1836
no ANC4+ -> ANC4+	wealth_num	0.1209	0.0224	1.1285	1.0800	1.1792
no ANC4+ -> ANC4+	urban	0.1335	0.0789	1.1428	0.9790	1.3339
ANC4+ -> facility delivery	(Intercept)	0.5197	0.0950	1.6815	1.3958	2.0256
ANC4+ -> facility delivery	wealth_num	0.2834	0.0322	1.3277	1.2464	1.4142
ANC4+ -> facility delivery	urban	0.6211	0.1485	1.8610	1.3909	2.4899
facility delivery -> postnatal check	(Intercept)	-3.2459	0.2155	0.0389	0.0255	0.0594
facility delivery -> postnatal check	wealth_num	0.0739	0.0698	1.0767	0.9391	1.2345
facility delivery -> postnatal check	urban	0.0469	0.2220	1.0480	0.6783	1.6191

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

6.6 What the surveys refused

Every card in this family completed on both surveys. That is a statement about the surveys: the recodes and variables these cards require were all present in both.

6.7 Where this family goes

Service demand for MATERNAL and DELIVERY (H-S-01), facility and workforce planning.

Table 37: Each card's declared integration target

#	Model	Integration target
8	Adequate ANC model	maternal service-demand planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
9	Early ANC initiation	maternal-risk prevention. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
10	Number of ANC contacts	service-volume forecasting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
11	Skilled birth attendance	workforce and maternal-care targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
12	Facility delivery	facility demand and transport link. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
13	Caesarean delivery	obstetric capacity planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
14	Postnatal care	continuum-of-care planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
15	Maternal continuum completion	identifies weakest maternal-care transition. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

6.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

> **THE RULE THAT APPLIES TO EVERY CARD IN PART II**
>
> Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

7. C. Fertility, Family Planning and Reproductive Health

Table 38: Fertility, Family Planning and Reproductive Health: the family at a glance

Cards in the family	**8**
Completed on Uganda 2016 DHS (UG2016DHS)	5
Completed on Kenya 2022 DHS (KE2022DHS)	5
Implemented in	`src/Models/fertility_fp/` — 8 Julia files
Downstream	The fertility term of the cohort-component projection (H-D-02) and commodity forecasting (H-SC-05).

7.1 What this family estimates

Children ever born, recent fertility, birth spacing, modern method use and method choice, unmet need, demand satisfied, and preference mismatch.

Fertility drives the population projection, and the population projection drives every service-need estimate downstream. Method choice drives the commodity bill. Both are in this family, and they are different models.

7.2 The trap

FAMILY C

A count of children ever born without an exposure offset compares a 45-year-old and a 20-year-old as though observed for the same length of time.

7.3 The models

All 8 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 39: Family C: the 8 model cards

#	Model	Outcome	Estimator	Ran	n
16	Children ever born	lifetime/parity count	Poisson/negative binomial	yes	18,506
17	Recent fertility	birth in reference period	survey logit	no	—
18	Birth spacing hazard	time to next birth	Cox/Weibull	yes	23,778
19	Modern contraceptive use	current modern method use	survey logit	yes	11,379
20	Contraceptive method choice	choice among method categories	multinomial/nested logit	yes	11,379
21	Unmet need model	unmet need for family planning	survey logit	yes	11,379
22	Demand satisfied model	demand for FP satisfied by modern methods	survey logit	no	—
23	Fertility preference mismatch	partner/woman preference disagreement	couple-level logit	no	—

7.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 40: Specification and inputs

#	Model	Core specification	Key inputs
16	Children ever born	E(CEB_i|X_i)=exp(X_iβ)	age, education, wealth, residence, union status
17	Recent fertility	Pr(Birth_i=1)=F(X_iβ)	age, parity, contraception, education, wealth
18	Birth spacing hazard	h_i(t)=h_0(t)exp(X_iβ)	parity, contraception, breastfeeding, child survival, education
19	Modern contraceptive use	Pr(MCPR_i=1)=F(X_iβ)	age, parity, education, wealth, fertility preference, partner variables
20	Contraceptive method choice	Pr(Method_i=j)=exp(X_iβ_j)/ Σ_k exp(X_iβ_k)	fertility preferences, demographics, access proxies
21	Unmet need model	Pr(Unmet_i=1)=F(X_iβ)	fertility intentions, union status, age, education, wealth
22	Demand satisfied model	Pr(DS_i=1)=F(X_iβ)	same plus partner/media factors
23	Fertility preference mismatch	Pr(Mismatch_i=1)=F(X_iβ)	couple-linked variables where available

7.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 41: What each card must report before its output is usable

#	Model	Diagnostics and validation
16	Children ever born	overdispersion and age exposure. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
17	Recent fertility	age-profile calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
18	Birth spacing hazard	PH test and censoring. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
19	Modern contraceptive use	method-definition sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
20	Contraceptive method choice	IIA/nesting tests. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
21	Unmet need model	DHS definition replication. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
22	Demand satisfied model	weighted calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
23	Fertility preference mismatch	linkage/sample-selection checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

7.5 What the committed runs produced

Table 42: Design-based indicators, Uganda 2016 DHS (UG2016DHS)

Indicator	Estimate	95 % CI	n	deff
Modern method use	34.8 %	33.4–36.1	11,379	2.32
Children ever born	308.2 %	301.9–314.4	18,506	nan

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

modern contraception coef

Survey logit, modern contraceptive use.

Table 43: modern contraception coef, Uganda 2016 DHS (UG2016DHS)

term	estimate	se	z	p	odds ratio	or low	or high
(Intercept)	-1.4018	0.1398	-10.0274	0.0000	0.2462	0.1872	0.3238
age	0.0135	0.0028	4.7424	0.0000	1.0136	1.0079	1.0192
edu_c: none	-0.6970	0.1295	-5.3830	0.0000	0.4981	0.3864	0.6420
edu_c: primary	-0.1335	0.0953	-1.3999	0.1615	0.8751	0.7259	1.0549
edu_c: secondary	-0.0092	0.1030	-0.0889	0.9292	0.9909	0.8097	1.2126
wealth_c: 2	0.4353	0.0771	5.6478	0.0000	1.5454	1.3287	1.7974
wealth_c: 3	0.5648	0.0842	6.7043	0.0000	1.7591	1.4913	2.0749
wealth_c: 4	0.6989	0.0894	7.8173	0.0000	2.0115	1.6882	2.3968
wealth_c: 5	0.6791	0.1126	6.0325	0.0000	1.9721	1.5816	2.4590
res_c: urban	0.0845	0.0822	1.0281	0.3039	1.0882	0.9262	1.2785

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

fertility poisson coef

Count model with an exposure offset. Without the offset every covariate would partly measure age.

Table 44: fertility poisson coef, Uganda 2016 DHS (UG2016DHS)

term	estimate	se	z	rate ratio	rr low	rr high
(Intercept)	-1.8547	0.0313	-59.2715	0.1565	0.1472	0.1664
edu_c: none	0.6417	0.0316	20.3232	1.8998	1.7858	2.0211
edu_c: primary	0.5942	0.0294	20.2407	1.8116	1.7103	1.9189
edu_c: secondary	0.3376	0.0308	10.9468	1.4015	1.3193	1.4889
wealth_c: 2	-0.0222	0.0137	-1.6173	0.9781	0.9522	1.0047
wealth_c: 3	-0.0495	0.0146	-3.3868	0.9517	0.9248	0.9794
wealth_c: 4	-0.0976	0.0168	-5.8249	0.9070	0.8777	0.9373
wealth_c: 5	-0.2274	0.0205	-11.0692	0.7966	0.7652	0.8293
res_c: urban	-0.1029	0.0168	-6.1138	0.9022	0.8730	0.9325

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

method choice coef

Multinomial, fitted as $J-1$ one-versus-base logits so that design-based standard errors remain tractable.

Table 45: method choice coef, Uganda 2016 DHS (UG2016DHS)

category	base	term	estimate	se	rrr	rrr low	rrr high
long_acting	none	(Intercept)	-3.2007	0.1866	0.0407	0.0283	0.0587
long_acting	none	age	0.0138	0.0045	1.0139	1.0049	1.0230
long_acting	none	wealth_num	0.1045	0.0409	1.1101	1.0247	1.2027
long_acting	none	edu_num	0.1525	0.0685	1.1648	1.0185	1.3320
other	none	(Intercept)	-6.1853	0.3156	0.0021	0.0011	0.0038
other	none	age	0.0454	0.0075	1.0464	1.0312	1.0619
other	none	wealth_num	0.4003	0.0558	1.4923	1.3378	1.6648
other	none	edu_num	0.2837	0.1057	1.3280	1.0795	1.6337
permanent	none	(Intercept)	-8.2503	0.2823	0.0003	0.0002	0.0005
permanent	none	age	0.1349	0.0056	1.1444	1.1319	1.1570
permanent	none	wealth_num	0.0918	0.0595	1.0961	0.9755	1.2317
permanent	none	edu_num	0.1236	0.0838	1.1315	0.9602	1.3335
short_acting	none	(Intercept)	-1.7798	0.1212	0.1687	0.1330	0.2139
short_acting	none	age	0.0016	0.0030	1.0016	0.9957	1.0076
short_acting	none	wealth_num	0.2027	0.0221	1.2247	1.1727	1.2789
short_acting	none	edu_num	0.2206	0.0386	1.2469	1.1560	1.3450

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

7.6 What the surveys refused

Table 46: Verbatim, from the catalogue summaries

#	Model	Survey	Reason the run gave
17	Recent fertility	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs a recent-birth (v208-derived) binary cohort builder
22	Demand satisfied model	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs a demand-satisfied composite (use ÷ (use+unmet)) cohort column
23	Fertility preference mis-match	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs the Couples recode (CR) and a couple-linked preference cohort

7.7 Where this family goes

The fertility term of the cohort-component projection (H-D-02) and commodity forecasting (H-SC-05).

Table 47: Each card's declared integration target

#	Model	Integration target
16	Children ever born	demographic projection inputs. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
17	Recent fertility	population and service-demand scenarios. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
18	Birth spacing hazard	fertility dynamics. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
19	Modern contraceptive use	family-planning targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
20	Contraceptive method choice	commodity and method-mix planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
21	Unmet need model	reproductive-health prioritization. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
22	Demand satisfied model	SDG-style monitoring. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
23	Fertility preference mismatch	gender-sensitive reproductive policy. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

7.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

> **THE RULE THAT APPLIES TO EVERY CARD IN PART II**
>
> Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

8. D. Child Nutrition and Growth

Table 48: Child Nutrition and Growth: the family at a glance

Cards in the family	**9**
Completed on Uganda 2016 DHS (UG2016DHS)	7
Completed on Kenya 2022 DHS (KE2022DHS)	6
Implemented in	`src/Models/child_nutrition/` — 9 Julia files
Downstream	Nutrition targeting, the agriculture-nutrition bridge, and the nutrition disability weight in the DALY calculation (H-O-03).

8.1 What this family estimates

Stunting, severe stunting, wasting and underweight; the continuous height-for-age and weight-for-height distributions; dietary diversity and acceptable diet; child anaemia severity.

Child nutrition is where the largest share of the preventable burden in the region sits, and it is measured, not reported: height and weight are taken with a board and a scale. That makes it unusually reliable — and unusually easy to ruin with a decode error.

8.2 The trap

FAMILY D

Anthropometric flag codes 9996–9999 encode 'out of range', 'age inconsistent', 'not measured' and 'not present'. Treated as numbers they produce a mean z-score in the thousands.

8.3 The models

All 9 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 49: Family D: the 9 model cards

#	Model	Outcome	Estimator	Ran	n
24	Stunting probability	height-for-age z<-2	survey logit/multilevel logit	yes	4,423
25	Severe stunting	HAZ<-3	survey rare-event logit	yes	4,423
26	Wasting probability	weight-for-height z<-2	survey logit	yes	4,413
27	Underweight probability	weight-for-age z<-2	survey logit	yes	4,441
28	Continuous HAZ model	height-for-age z score	survey-weighted linear/multilevel model	yes	4,423
29	Continuous WHZ model	weight-for-height z score	linear/multilevel model	yes	4,413
30	Minimum dietary diversity	child meets MDD	survey logit	no	—
31	Minimum acceptable diet	child meets MAD	survey logit	no	—
32	Child anaemia severity	none/mild/moderate/severe	ordered logit/probit	yes	3,944

8.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 50: Specification and inputs

#	Model	Core specification	Key inputs
24	Stunting probability	Pr(Stunt_i=1)=F(X_iβ)	age, sex, birth size, maternal BMI/education, wealth, WASH, feeding
25	Severe stunting	Pr(SevereStunt_i=1)=F(X_iβ)	same
26	Wasting probability	Pr(Waste_i=1)=F(X_iβ)	recent illness, feeding, WASH, household factors
27	Underweight probability	Pr(UW_i=1)=F(X_iβ)	child, maternal and household factors
28	Continuous HAZ model	HAZ_i=X_iβ+u_c+ε_i	child, maternal, household, cluster factors
29	Continuous WHZ model	WHZ_i=X_iβ+u_c+ε_i	illness, feeding, WASH, wealth
30	Minimum dietary diversity	Pr(MDD_i=1)=F(X_iβ)	age, breastfeeding, maternal education, wealth, media
31	Minimum acceptable diet	Pr(MAD_i=1)=F(X_iβ)	feeding and household covariates
32	Child anaemia severity	Pr(Y_i$\leq$j)=F(κ_j-X_iβ)	diet, malaria, age, maternal anaemia, wealth

8.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 51: What each card must report before its output is usable

#	Model	Diagnostics and validation
24	Stunting probability	anthropometric flagging, age calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
25	Severe stunting	rare-event calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
26	Wasting probability	season/survey-month sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
27	Underweight probability	age calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
28	Continuous HAZ model	residuals, nonlinearity, cluster ICC. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
29	Continuous WHZ model	outlier and residual diagnostics. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
30	Minimum dietary diversity	indicator-definition validation. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
31	Minimum acceptable diet	indicator consistency. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
32	Child anaemia severity	parallel-lines test. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

8.5 What the committed runs produced

Table 52: Design-based indicators, Uganda 2016 DHS (UG2016DHS)

Indicator	Estimate	95 % CI	n	deff
Stunting (HAZ < −2)	28.2 %	26.5–29.9	4,423	1.66
Wasting (WHZ < −2)	3.8 %	3.1–4.4	4,413	1.33
Child anaemia, any	53.8 %	51.5–56.0	3,944	2.13

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

The wealth gradient

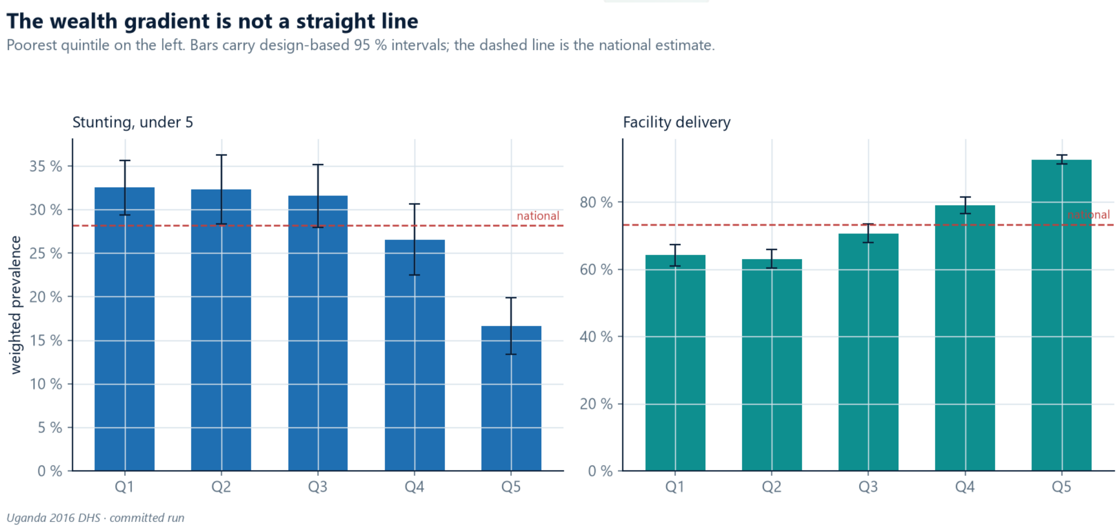
Table 53: Stunting by wealth quintile, Uganda 2016 DHS (UG2016DHS)

Quintile	Stunting	95 % CI	n
Q1	32.5 %	29.4–35.6	1,187
Q2	32.3 %	28.3–36.3	936
Q3	31.6 %	28.0–35.2	868
Q4	26.6 %	22.5–30.6	768
Q5	16.6 %	13.4–19.9	664

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

The gradient is flat across the bottom four quintiles and falls only at the top. A linear wealth term would have reported a smooth gradient that is not there, and a programme targeted on the bottom two quintiles would be targeting a group that is indistinguishable from the middle two.

Figure 8: Stunting by wealth quintile with design-based intervals



Notes: The gradient is flat across the bottom four quintiles and falls only at the top — a pattern a linear wealth term would have hidden. Source: Uganda 2016 DHS · committed run.

stunting coef

Survey logit, stunting. Reference categories are wealth quintile 1, higher education and rural residence.

Table 54: stunting coef, Uganda 2016 DHS (UG2016DHS)

term	estimate	se	z	p	odds ratio	or low	or high
(Intercept)	-1.9827	0.2668	-7.4314	0.0000	0.1377	0.0816	0.2323
wealth_c: 2	0.0294	0.1164	0.2521	0.8010	1.0298	0.8197	1.2938
wealth_c: 3	0.0033	0.1175	0.0282	0.9775	1.0033	0.7970	1.2630
wealth_c: 4	-0.1765	0.1351	-1.3067	0.1913	0.8382	0.6433	1.0922
wealth_c: 5	-0.6232	0.1754	-3.5535	0.0004	0.5362	0.3802	0.7562
edu_c: none	1.3002	0.2850	4.5621	0.0000	3.6702	2.0993	6.4164
edu_c: primary	0.9970	0.2609	3.8216	0.0001	2.7101	1.6252	4.5193
edu_c: secondary	0.8290	0.2830	2.9296	0.0034	2.2911	1.3157	3.9896
res_c: urban	0.0935	0.1394	0.6711	0.5022	1.0980	0.8356	1.4429
age_months	0.0069	0.0021	3.3782	0.0007	1.0069	1.0029	1.0110

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

haz quantile coef

Quantile regression on height-for-age. A covariate can move the tenth percentile while leaving the median almost unchanged, and it is the lower tail that crosses -2.

Table 55: haz quantile coef, Uganda 2016 DHS (UG2016DHS)

tau	term	estimate	se	ci low	ci high
0.1000	(Intercept)	-3.3710	0.1544	-3.6736	-3.0684
0.1000	wealth_num	0.1484	0.0394	0.0711	0.2257
0.1000	urban	0.1183	0.1266	-0.1298	0.3664
0.1000	age_months	0.0006	0.0029	-0.0050	0.0062
0.2500	(Intercept)	-2.3466	0.1198	-2.5813	-2.1119
0.2500	wealth_num	0.1390	0.0315	0.0773	0.2007
0.2500	urban	0.0644	0.0887	-0.1095	0.2382
0.2500	age_months	-0.0057	0.0023	-0.0102	-0.0012
0.5000	(Intercept)	-1.3021	0.0721	-1.4433	-1.1609
0.5000	wealth_num	0.1123	0.0263	0.0607	0.1638
0.5000	urban	0.0817	0.0968	-0.1080	0.2714
0.5000	age_months	-0.0101	0.0015	-0.0131	-0.0071
0.7500	(Intercept)	-0.1768	0.1169	-0.4059	0.0523
0.7500	wealth_num	0.0852	0.0344	0.0177	0.1526
0.7500	urban	0.0650	0.1025	-0.1360	0.2659
0.7500	age_months	-0.0154	0.0018	-0.0190	-0.0118
0.9000	(Intercept)	0.6552	0.1575	0.3465	0.9640
0.9000	wealth_num	0.1146	0.0386	0.0389	0.1903
0.9000	urban	0.1174	0.1876	-0.2504	0.4851
0.9000	age_months	-0.0164	0.0026	-0.0214	-0.0113

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

8.6 What the surveys refused

Table 56: Verbatim, from the catalogue summaries

#	Model	Survey	Reason the run gave
30	Minimum dietary diversity	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs an IYCF food-group cohort (v409–v414/v410–v414) — not yet built
31	Minimum acceptable diet	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs an IYCF feeding-frequency + diversity cohort — not yet built
32	Child anaemia severity	Kenya 2022 DHS	eligible sample 0 < disclosure threshold 25

8.7 Where this family goes

Nutrition targeting, the agriculture-nutrition bridge, and the nutrition disability weight in the DALY calculation (H-O-03).

Table 57: Each card's declared integration target

#	Model	Integration target
24	Stunting probability	nutrition targeting and agriculture linkage. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
25	Severe stunting	high-priority nutrition targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
26	Wasting probability	food/crisis response. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
27	Underweight probability	integrated nutrition monitoring. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
28	Continuous HAZ model	growth-faltering simulations. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
29	Continuous WHZ model	acute nutrition analysis. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
30	Minimum dietary diversity	agriculture-food-system linkage. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
31	Minimum acceptable diet	nutrition intervention scenarios. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
32	Child anaemia severity	nutrition-malaria integrated planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

8.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

THE RULE THAT APPLIES TO EVERY CARD IN PART II

Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

9. E. Maternal and Adult Nutrition and Anaemia

Table 58: Maternal and Adult Nutrition and Anaemia: the family at a glance

Cards in the family	**5**
Completed on Uganda 2016 DHS (UG2016DHS)	5
Completed on Kenya 2022 DHS (KE2022DHS)	3
Implemented in	`src/Models/maternal_nutrition/` — 5 Julia files
Downstream	Maternal disease burden and the maternal component of the health-system bridge.

9.1 What this family estimates

Women's body-mass index, underweight, overweight and obesity, anaemia, and anaemia severity as an ordered outcome.

Adult and maternal nutrition carries the double burden — underweight and obesity in the same population, sometimes in the same household. A single mean hides it; this family does not.

9.2 The trap

FAMILY E

Biomarker measurement has its own eligibility and its own weight. A biomarker denominator is not the women's-file denominator.

9.3 The models

All 5 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 59: Family E: the 5 model cards

#	Model	Outcome	Estimator	Ran	n
33	Women's BMI model	continuous BMI	survey linear/quantile regression	yes	6,049
34	Women's underweight	BMI<18.5	survey logit	yes	6,049
35	Women's overweight/obesity	BMI≥25/30	survey logit/multinomial	yes	6,049
36	Women's anaemia	anaemia status	survey logit	yes	6,031
37	Anaemia severity ordered model	severity category	ordered logit/probit	yes	6,031

9.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 60: Specification and inputs

#	Model	Core specification	Key inputs
33	Women's BMI model	BMI_i=X_iβ+ε_i	age, parity, education, wealth, residence
34	Women's underweight	Pr(UW_i=1)=F(X_iβ)	demographic and socioeconomic factors
35	Women's overweight/obesity	Pr(OW_i=1)=F(X_iβ)	age, parity, wealth, urbanicity, education
36	Women's anaemia	Pr(Anaemia_i=1)=F(X_iβ)	pregnancy, parity, nutrition, malaria context, wealth
37	Anaemia severity ordered model	Pr(Y_i$\leq$j)=F(κ_j-X_iβ)	same

9.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 61: What each card must report before its output is usable

#	Model	Diagnostics and validation
33	Women's BMI model	nonlinearity and outliers. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
34	Women's underweight	calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
35	Women's overweight/obesity	threshold sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
36	Women's anaemia	biomarker/sample checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
37	Anaemia severity ordered model	parallel-lines test. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

9.5 What the committed runs produced

anaemia ordinal coef

Proportional-odds ordinal model for anaemia severity. The assumption is tested rather than assumed.

Table 62: anaemia ordinal coef, Uganda 2016 DHS (UG2016DHS)

term	estimate	se	z	odds ratio	or low	or high
threshold_1	-1.9500	0.1150	-16.9635	0.1423	0.1136	0.1782
threshold_2	-0.8245	0.0332	-24.8151	0.4384	0.4108	0.4679
threshold_3	2.1962	0.0418	52.5470	8.9911	8.2840	9.7587
age_months	-0.0368	0.0023	-16.0684	0.9639	0.9596	0.9682
wealth_num	-0.2173	0.0299	-7.2733	0.8047	0.7589	0.8532

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

9.6 What the surveys refused

Table 63: Verbatim, from the catalogue summaries

#	Model	Survey	Reason the run gave
36	Women's anaemia	Kenya 2022 DHS	eligible sample 0 < disclosure threshold 25
37	Anaemia severity ordered model	Kenya 2022 DHS	eligible sample 0 < disclosure threshold 25

9.7 Where this family goes

Maternal disease burden and the maternal component of the health-system bridge.

Table 64: Each card's declared integration target

#	Model	Integration target
33	Women's BMI model	NCD/nutrition transition module. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
34	Women's underweight	maternal nutrition targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
35	Women's overweight/obesity	NCD prevention planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
36	Women's anaemia	maternal nutrition and productivity linkage. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
37	Anaemia severity ordered model	resource targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

9.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

THE RULE THAT APPLIES TO EVERY CARD IN PART II

Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

10. F. Child Morbidity and Treatment

Table 65: Child Morbidity and Treatment: the family at a glance

Cards in the family	**6**
Completed on Uganda 2016 DHS (UG2016DHS)	3
Completed on Kenya 2022 DHS (KE2022DHS)	3
Implemented in	`src/Models/child_morbidity/` — 6 Julia files
Downstream	Incidence and treatment coverage in the endemic disease engine (H-E-03, H-O-01).

10.1 What this family estimates

Fever, acute respiratory infection symptoms and diarrhoea; care seeking; oral rehydration and appropriate fever treatment.

Child morbidity is what fills an outpatient department. The prevalence cards feed the demand model; the care-seeking and treatment cards say what share of that demand reaches a facility, and what share is treated correctly when it does.

10.2 The trap

FAMILY F

Care-seeking and treatment are asked only of children reported ill. A blank is not missing — the filter defines the value.

10.3 The models

All 6 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 66: Family F: the 6 model cards

#	Model	Outcome	Estimator	Ran	n
38	Fever prevalence	recent fever	survey logit	yes	4,527
39	ARI symptoms	acute respiratory infection symptoms	survey logit	yes	4,527
40	Diarrhoea prevalence	recent diarrhoea	survey logit/multilevel	yes	4,523
41	Care seeking for fever/ARI	care sought from appropriate provider	survey logit	no	—
42	ORS treatment	ORS for diarrhoea	survey logit	no	—
43	Appropriate fever treatment	appropriate antimalarial where measurable	survey logit	no	—

10.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 67: Specification and inputs

#	Model	Core specification	Key inputs
38	Fever prevalence	Pr(Fever_i=1)=F(X_iβ)	age, season, housing, bednet, wealth, region
39	ARI symptoms	Pr(ARI_i=1)=F(X_iβ)	age, cooking fuel, housing, nutrition, wealth
40	Diarrhoea prevalence	Pr(Diarr_i=1)=F(X_iβ)	water, sanitation, age, feeding, wealth
41	Care seeking for fever/ARI	Pr(Care_i=1)=F(X_iβ)	severity proxies, mother education, wealth, residence, barriers
42	ORS treatment	Pr(ORS_i=1)=F(X_iβ)	care seeking, education, wealth, residence
43	Appropriate fever treatment	Pr(Treat_i=1)=F(X_iβ)	testing, care source, wealth, region

10.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 68: What each card must report before its output is usable

#	Model	Diagnostics and validation
38	Fever prevalence	recall and season sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
39	ARI symptoms	symptom-definition sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
40	Diarrhoea prevalence	WASH definition checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
41	Care seeking for fever/ARI	conditional-sample checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
42	ORS treatment	treatment-definition checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
43	Appropriate fever treatment	country/year protocol sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

10.5 What the committed runs produced

Table 69: Design-based indicators, Uganda 2016 DHS (UG2016DHS)

Indicator	Estimate	95 % CI	n	deff
Fever in the last two weeks	37.3 %	35.1–39.4	4,527	2.26

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

fever 2w coef

Survey logit, fever in the last two weeks.

Table 70: fever 2w coef, Uganda 2016 DHS (UG2016DHS)

term	estimate	se	z	p	odds ratio	or low	or high
(Intercept)	0.0240	0.2346	0.1023	0.9185	1.0243	0.6468	1.6222
wealth_c: 2	-0.4594	0.1168	-3.9351	0.0001	0.6316	0.5024	0.7941
wealth_c: 3	-0.6052	0.1296	-4.6698	0.0000	0.5460	0.4235	0.7038
wealth_c: 4	-0.4288	0.1324	-3.2398	0.0012	0.6513	0.5025	0.8442
wealth_c: 5	-1.1960	0.1933	-6.1882	0.0000	0.3024	0.2071	0.4417
edu_c: none	0.1467	0.2462	0.5958	0.5513	1.1580	0.7147	1.8760
edu_c: primary	-0.0026	0.2208	-0.0120	0.9904	0.9974	0.6470	1.5374
edu_c: secondary	-0.0554	0.2189	-0.2532	0.8001	0.9461	0.6160	1.4531
res_c: urban	-0.2495	0.1586	-1.5733	0.1157	0.7792	0.5711	1.0632
age_months	-0.0002	0.0022	-0.0929	0.9259	0.9998	0.9955	1.0041

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

10.6 What the surveys refused

Table 71: Verbatim, from the catalogue summaries

#	Model	Survey	Reason the run gave
41	Care seeking for fever/ARI	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs a care-seeking outcome (h32*) conditional cohort — not yet built
42	ORS treatment	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs an ORS (h13) treatment conditional cohort — not yet built
43	Appropriate fever treatment	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs an antimalarial (ml13*) treatment conditional cohort — not yet built

10.7 Where this family goes

Incidence and treatment coverage in the endemic disease engine (H-E-03, H-O-01).

Table 72: Each card's declared integration target

#	Model	Integration target
38	Fever prevalence	disease surveillance proxy. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
39	ARI symptoms	energy-health linkage. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
40	Diarrhoea prevalence	WASH investment analysis. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
41	Care seeking for fever/ARI	health-service demand. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
42	ORS treatment	commodity planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
43	Appropriate fever treatment	malaria programme evaluation. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

10.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

> **THE RULE THAT APPLIES TO EVERY CARD IN PART II**
>
> Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

11. G. Immunization and Preventive Child Health

Table 73: Immunization and Preventive Child Health: the family at a glance

Cards in the family	**6**
Completed on Uganda 2016 DHS (UG2016DHS)	5
Completed on Kenya 2022 DHS (KE2022DHS)	4
Implemented in	`src/Models/immunization/` — 6 Julia files
Downstream	The prevention factor in the epidemiology engine (H-E-05) and cold-chain commodity planning.

11.1 What this family estimates

Full basic immunization, zero-dose children, DTP dropout, measles, timeliness, and bednet use.

Immunisation is the cheapest intervention in the estate and the one with the clearest coverage target. The zero-dose card is the one a programme acts on: it identifies children the system has never touched at all.

11.2 The trap

> **FAMILY G**
>
> Zero-dose prevalence is a few per cent, so a regression on it rests on very few events even in a large survey — and it is the family most likely to produce a singleton stratum.

11.3 The models

All 6 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 74: Family G: the 6 model cards

#	Model	Outcome	Estimator	Ran	n
44	Full basic immunization	child fully immunized	survey logit/multilevel	yes	953
45	Zero-dose child model	no DTP-containing dose	survey logit	yes	953
46	DTP dropout	DTP1 to DTP3 dropout	survey logit	yes	907
47	Measles vaccination	measles-containing vaccine receipt	survey logit	yes	953
48	Vaccination timeliness	age at vaccine receipt	survival/event-history model	no	—
49	Bednet use by child	slept under ITN	survey logit	yes	4,796

11.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 75: Specification and inputs

#	Model	Core specification	Key inputs
44	Full basic immunization	Pr(FullImm_i=1)=F(X_iβ)	maternal education, ANC, facility delivery, wealth, residence
45	Zero-dose child model	Pr(Zero_i=1)=F(X_iβ)	maternal, household, access factors
46	DTP dropout	Pr(Drop_i=1|DTP1)=F(X_iβ)	access, maternal care, wealth, mobility
47	Measles vaccination	Pr(MCV_i=1)=F(X_iβ)	same
48	Vaccination timeliness	h_i(t)=h_0(t)exp(X_iβ)	vaccination dates, maternal/household factors
49	Bednet use by child	Pr(ITN_i=1)=F(X_iβ)	household net ownership, age, wealth, region

11.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 76: What each card must report before its output is usable

#	Model	Diagnostics and validation
44	Full basic immunization	card/recall sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
45	Zero-dose child model	definition and age-cohort checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
46	DTP dropout	conditional cohort validation. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
47	Measles vaccination	age eligibility checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
48	Vaccination timeliness	date-quality checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
49	Bednet use by child	ownership-use decomposition. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

11.5 What the committed runs produced

Table 77: Design-based indicators, Uganda 2016 DHS (UG2016DHS)

Indicator	Estimate	95 % CI	n	deff
Zero-dose child	5.5 %	3.7–7.4	953	1.62

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

zero dose coef

Survey logit, zero-dose children — the rare-event case.

Table 78: zero dose coef, Uganda 2016 DHS (UG2016DHS)

term	estimate	se	z	p	odds ratio	or low	or high
(Intercept)	-5.3444	1.6702	-3.1998	0.0014	0.0048	0.0002	0.1261
wealth_c: 2	1.0547	0.5741	1.8371	0.0662	2.8712	0.9319	8.8465
wealth_c: 3	0.7076	0.5687	1.2444	0.2134	2.0292	0.6657	6.1857
wealth_c: 4	1.0294	0.6048	1.7021	0.0887	2.7994	0.8556	9.1595
wealth_c: 5	0.4120	0.7106	0.5797	0.5621	1.5098	0.3750	6.0790
edu_c: none	2.2682	1.2133	1.8694	0.0616	9.6618	0.8959	104.2009
edu_c: primary	0.9908	1.1467	0.8640	0.3876	2.6934	0.2846	25.4916
edu_c: secondary	0.9709	1.1832	0.8206	0.4119	2.6403	0.2597	26.8418
res_c: urban	0.1494	0.4812	0.3104	0.7562	1.1611	0.4521	2.9817
age_months	0.0367	0.0654	0.5610	0.5748	1.0373	0.9126	1.1791

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

11.6 What the surveys refused

Table 79: Verbatim, from the catalogue summaries

#	Model	Survey	Reason the run gave
48	Vaccination timeliness	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs a vaccination-date event-history cohort (h3d/h5d/h9d) — not yet built
49	Bednet use by child	Kenya 2022 DHS	eligible sample 0 < disclosure threshold 25

11.7 Where this family goes

The prevention factor in the epidemiology engine (H-E-05) and cold-chain commodity planning.

Table 80: Each card's declared integration target

#	Model	Integration target
44	Full basic immunization	vaccination targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
45	Zero-dose child model	priority outreach. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
46	DTP dropout	continuity of immunization. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
47	Measles vaccination	campaign planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
48	Vaccination timeliness	cold-chain/outreach planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
49	Bednet use by child	malaria prevention. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

11.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

> **THE RULE THAT APPLIES TO EVERY CARD IN PART II**
>
> Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

12. H. Malaria, HIV and Biomarker Models

Table 81: Malaria, HIV and Biomarker Models: the family at a glance

Cards in the family	**6**
Completed on Uganda 2016 DHS (UG2016DHS)	1
Completed on Kenya 2022 DHS (KE2022DHS)	0
Implemented in	`src/Models/malaria_hiv/` — 6 Julia files
Downstream	Disease-specific incidence and case-fatality in the burden engine, and the malaria climate envelope (H-CL-02).

12.1 What this family estimates

Parasitaemia, the malaria-anaemia joint risk, HIV prevalence, testing uptake, comprehensive knowledge and stigma.

Malaria and HIV are measured by biomarker rather than by report, on a subsample with its own weight. They carry the largest single-disease burdens in the region and the strictest governance conditions in the estate.

12.2 The trap

> **FAMILY H**
>
> HIV and biomarker cards require both a configuration flag and a recorded ethics approval reference. A flag alone is not enough.

12.3 The models

All 6 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 82: Family H: the 6 model cards

#	Model	Outcome	Estimator	Ran	n
50	Malaria parasitaemia	positive malaria test where available	survey/multilevel logit	yes	4,796
51	Malaria anaemia joint-risk	anaemia conditional on malaria status	survey logit	no	—
52	HIV prevalence	HIV positive where biomarker available	biomarker-weighted logit	no	—
53	HIV testing uptake	ever/recently tested	survey logit	no	—
54	Comprehensive HIV knowledge	knowledge indicator	survey logit	no	—
55	HIV stigma attitude model	stigma index/category	ordered/latent-variable model	no	—

12.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 83: Specification and inputs

#	Model	Core specification	Key inputs
50	Malaria parasitaemia	Pr(Mal_i=1)=F(X_iβ)	age, ITN, housing, wealth, cluster, season
51	Malaria anaemia joint-risk	Pr(Anaemia_i=1)=F(βMalaria_i+X_iγ)	malaria test, nutrition and household factors
52	HIV prevalence	Pr(HIV_i=1)=F(X_iβ)	age, sex, union history, testing, behaviour proxies, wealth
53	HIV testing uptake	Pr(Test_i=1)=F(X_iβ)	knowledge, age, sex, education, wealth, union status
54	Comprehensive HIV knowledge	Pr(Know_i=1)=F(X_iβ)	education, media, age, wealth, residence
55	HIV stigma attitude model	Pr(Y_i$\leq$j)=F(κ_j-X_iβ)	education, knowledge, media, demographics

12.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 84: What each card must report before its output is usable

#	Model	Diagnostics and validation
50	Malaria parasitaemia	biomarker subsample weights, calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
51	Malaria anaemia joint-risk	confounding sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
52	HIV prevalence	nonresponse and biomarker weights. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
53	HIV testing uptake	country question harmonization. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
54	Comprehensive HIV knowledge	indicator-definition checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
55	HIV stigma attitude model	scale reliability. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

12.5 What the committed runs produced

Table 85: Design-based indicators, Uganda 2016 DHS (UG2016DHS)

Indicator	Estimate	95 % CI	n	deff
Malaria, rapid diagnostic test	30.3 %	27.9–32.7	4,796	3.46

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

12.6 What the surveys refused

Table 86: Verbatim, from the catalogue summaries

#	Model	Survey	Reason the run gave
50	Malaria parasitaemia	Kenya 2022 DHS	eligible sample 0 < disclosure threshold 25
51	Malaria anaemia joint-risk	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs a merged malaria+anaemia biomarker cohort (hml32+hml35+hc57/ha57) — not yet built
52	HIV prevalence	Uganda 2016 DHS, Kenya 2022 DHS	recode AR not found
53	HIV testing uptake	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs an HIV-testing cohort (v781/v826) — not yet built
54	Comprehensive HIV knowledge	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs an HIV-knowledge composite cohort (v754*/v756) — not yet built
55	HIV stigma attitude model	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs an HIV-stigma scale cohort (v857*) — not yet built

12.7 Where this family goes

Disease-specific incidence and case-fatality in the burden engine, and the malaria climate envelope (H-CL-02).

Table 87: Each card's declared integration target

#	Model	Integration target
50	Malaria parasitaemia	climate-malaria spatial module. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
51	Malaria anaemia joint-risk	integrated disease-nutrition policy. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
52	HIV prevalence	HIV resource targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
53	HIV testing uptake	testing strategy. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
54	Comprehensive HIV knowledge	communication strategy. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
55	HIV stigma attitude model	behaviour-change module. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

12.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

> **THE RULE THAT APPLIES TO EVERY CARD IN PART II**
>
> Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

13. I. WASH, Household Environment and Environmental Health

Table 88: WASH, Household Environment and Environmental Health: the family at a glance

Cards in the family	**6**
Completed on Uganda 2016 DHS (UG2016DHS)	6
Completed on Kenya 2022 DHS (KE2022DHS)	6
Implemented in	`src/Models/wash_env/` — 6 Julia files
Downstream	The energy bridge (clean cooking), WASH investment planning, and the environmental risk factor in the population attributable fraction (H-E-10).

13.1 What this family estimates

Improved water and sanitation, open defecation, the clean-cooking transition, an environmental health index, and the WASH-diarrhoea association.

Water, sanitation and household air are risk factors rather than outcomes, and they belong to ministries other than health. This family is where the health estate states what it needs from them, and what a change in them would do.

13.2 The trap

> **FAMILY I**
>
> Water and sanitation must be mapped to the JMP service ladders. An ad-hoc grouping is not comparable with any published figure.

13.3 The models

All 6 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 89: Family I: the 6 model cards

#	Model	Outcome	Estimator	Ran	n
56	Improved drinking water	household has improved source	survey logit	yes	19,588
57	Improved sanitation	improved sanitation	survey logit	yes	19,588
58	Open defecation	household practices open defecation	survey logit	yes	19,588
59	Clean cooking transition	clean versus polluting fuel	survey logit/multinomial	yes	19,588
60	Household environmental health index	latent/indexed environmental deprivation	PCA/factor analysis	yes	19,588
61	WASH–diarrhoea association	child diarrhoea conditional on WASH	survey logit/multilevel	yes	4,523

13.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 90: Specification and inputs

#	Model	Core specification	Key inputs
56	Improved drinking water	Pr(Water_i=1)=F(X_iβ)	wealth, residence, region, household structure
57	Improved sanitation	Pr(San_i=1)=F(X_iβ)	wealth, residence, region
58	Open defecation	Pr(OD_i=1)=F(X_iβ)	wealth, residence, education, region
59	Clean cooking transition	Pr(Clean_i=1)=F(X_iβ)	wealth, electricity, residence, household size
60	Household environmental health index	EHI_i=Σ_k ω_k D_{ik}	water, sanitation, fuel, housing materials, crowding
61	WASH–diarrhoea association	Pr(Diarr_i=1)=F(βWASH_i+X_iγ)	WASH variables plus confounders

13.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 91: What each card must report before its output is usable

#	Model	Diagnostics and validation
56	Improved drinking water	JMP classification checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
57	Improved sanitation	shared-facility definition sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
58	Open defecation	classification checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
59	Clean cooking transition	fuel-category sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
60	Household environmental health index	KMO/reliability/robustness. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
61	WASH–diarrhoea association	interaction and confounding sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

13.5 What the committed runs produced

No indicator table from this family is shipped in `08_Data/`. The cards that completed wrote coefficient tables and model cards rather than headline indicators; Appendix K carries every coefficient table the run produced.

13.6 What the surveys refused

Every card in this family completed on both surveys. That is a statement about the surveys: the recodes and variables these cards require were all present in both.

13.7 Where this family goes

The energy bridge (clean cooking), WASH investment planning, and the environmental risk factor in the population attributable fraction (H-E-10).

Table 92: Each card's declared integration target

#	Model	Integration target
56	Improved drinking water	infrastructure-poverty integration. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/ Arrow/Parquet and documented bridge tables
57	Improved sanitation	WASH investment targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/ Parquet and documented bridge tables
58	Open defecation	sanitation prioritization. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/ Parquet and documented bridge tables
59	Clean cooking transition	energy-health module. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/ Parquet and documented bridge tables
60	Household environmental health index	poverty, climate and health vulnerability. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
61	WASH–diarrhoea association	benefit parameter for WASH scenarios. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

13.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

> **THE RULE THAT APPLIES TO EVERY CARD IN PART II**
>
> Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

14. J. Women's Empowerment, Gender and Violence-Related Health

Table 93: Women's Empowerment, Gender and Violence-Related Health: the family at a glance

Cards in the family	**5**
Completed on Uganda 2016 DHS (UG2016DHS)	0
Completed on Kenya 2022 DHS (KE2022DHS)	0
Implemented in	`src/Models/empowerment_gender/` — 5 Julia files
Downstream	Gender-responsive programme design and the empowerment index used by the poverty and education bridges.

14.1 What this family estimates

Household decision-making, empowerment and maternal care, employment and reproductive health, intimate partner violence risk and its relation to service use.

Decision-making power, employment and violence are determinants of care-seeking that no clinical model contains. They are also the family with the strictest ethics conditions and, on the pilot survey, the family that ran the least.

14.2 The trap

FAMILY J

The domestic-violence module is restricted, its subsample has its own weight, and on the pilot survey this family completed no cards at all.

14.3 The models

All 5 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 94: Family J: the 5 model cards

#	Model	Outcome	Estimator	Ran	n
62	Household decision-making index	latent empowerment score	PCA/factor/IRT	no	—
63	Empowerment and maternal care	maternal service use conditional on empowerment	survey logit/SEM	no	—
64	Employment and reproductive health	modern contraception/ANC by employment	survey logit	no	—
65	Intimate partner violence risk	IPV indicator where DV module available	DV-weighted logit	no	—
66	IPV and health-service use	service use conditional on IPV exposure	DV-weighted logit	no	—

14.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 95: Specification and inputs

#	Model	Core specification	Key inputs
62	Household decision-making index	$Emp\_i=\Sigma\_k\ \lambda\_k\ D\_\{ik\}+\varepsilon\_i$	decisions on health, purchases, visits, earnings
63	Empowerment and maternal care	$Pr(Care\_i=1)=F(\beta Emp\_i+X\_i\gamma)$	empowerment plus socioeconomic controls
64	Employment and reproductive health	$Pr(Y\_i=1)=F(\beta Work\_i+X\_i\gamma)$	employment, earnings control, demographics
65	Intimate partner violence risk	$Pr(IPV\_i=1)=F(X\_i\beta)$	age, union characteristics, partner alcohol proxies, empowerment
66	IPV and health-service use	$Pr(Care\_i=1)=F(\beta IPV\_i+X\_i\gamma)$	IPV, autonomy, wealth, access

14.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 96: What each card must report before its output is usable

#	Model	Diagnostics and validation
62	Household decision-making index	reliability and measurement invariance. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
63	Empowerment and maternal care	endogeneity caveat, mediation sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
64	Employment and reproductive health	selection sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
65	Intimate partner violence risk	DV subsample weights and ethics checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
66	IPV and health-service use	selection/confounding sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

14.5 What the committed runs produced

empowerment loadings

Factor loadings for the empowerment index. The index is a latent construct and its scale is arbitrary.

Table 97: empowerment loadings, Uganda 2016 DHS (UG2016DHS)

item	loading	communality	share of component
dec_v743a	0.1946	0.0379	0.0379
dec_v743b	0.1860	0.0346	0.0346
dec_v743d	0.1984	0.0394	0.0394
owns_v745a	0.0300	0.0009	0.0009
owns_v745b	0.0551	0.0030	0.0030
earns_cash	0.1334	0.0178	0.0178
rej_v744a	0.4259	0.1814	0.1814
rej_v744b	0.4323	0.1869	0.1869
rej_v744c	0.4447	0.1978	0.1978
rej_v744d	0.4034	0.1627	0.1627
rej_v744e	0.3712	0.1378	0.1378

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

14.6 What the surveys refused

Table 98: Verbatim, from the catalogue summaries

#	Model	Survey	Reason the run gave
62	Household decision-making index	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs an empowerment-score (v743*) index cohort — not yet built
63	Empowerment and maternal care	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs empowerment score merged to maternal-care outcomes — not yet built
64	Employment and reproductive health	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs an employment (v714/v731) covariate cohort — not yet built
65	Intimate partner violence risk	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs the DV-module (d105*) subsample cohort with DV weights — not yet built
66	IPV and health-service use	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs DV module merged to service-use outcomes — not yet built

14.7 Where this family goes

Gender-responsive programme design and the empowerment index used by the poverty and education bridges.

Table 99: Each card's declared integration target

#	Model	Integration target
62	Household decision-making index	gender-health pathway. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
63	Empowerment and maternal care	gender policy scenarios. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
64	Employment and reproductive health	labour-gender-health linkage. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
65	Intimate partner violence risk	gender vulnerability analysis. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
66	IPV and health-service use	gender-responsive service planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

14.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

THE RULE THAT APPLIES TO EVERY CARD IN PART II

Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

15. K. Health Insurance, Access Barriers and Service Choice

Table 100: Health Insurance, Access Barriers and Service Choice: the family at a glance

Cards in the family	**4**
Completed on Uganda 2016 DHS (UG2016DHS)	2
Completed on Kenya 2022 DHS (KE2022DHS)	1
Implemented in	`src/Models/insurance_access/` — 4 Julia files
Downstream	The demand side of facility planning (H-A-06 Huff choice) and the out-of-pocket module of the poverty microsimulation (H-P-01).

15.1 What this family estimates

Insurance coverage, reported barriers to access, provider choice for child illness, and facility-delivery choice.

Insurance, barriers and provider choice are the demand side of the health system. They are what a financing reform changes, and they connect Part II to the poverty microsimulation in Chapter 30.

15.2 The trap

FAMILY K

Provider and facility choice are unordered alternatives. Collapsing them to a binary hides the substitution between public, private and informal providers that a financing reform turns on.

15.3 The models

All 4 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 101: Family K: the 4 model cards

#	Model	Outcome	Estimator	Ran	n
67	Health insurance coverage	insured indicator	survey logit	yes	18,506
68	Reported access barriers	any serious barrier to care	survey logit/ordered model	no	—
69	Provider choice for child illness	public/private/pharmacy/other/no care	multinomial/nested logit	no	—
70	Facility delivery choice	public/private/home/other	multinomial logit	yes	15,522

15.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 102: Specification and inputs

#	Model	Core specification	Key inputs
67	Health insurance coverage	Pr(Ins_i=1)=F(X_iβ)	wealth, employment, education, residence, age
68	Reported access barriers	Pr(Barrier_i=1)=F(X_iβ)	permission, money, distance, accompaniment, demographics
69	Provider choice for child illness	Pr(Choice_i=j)=exp(X_iβ_j)/Σ_k exp(X_iβ_k)	illness, wealth, residence, maternal education
70	Facility delivery choice	Pr(Choice_i=j)=exp(X_iβ_j)/Σ_k exp(X_iβ_k)	wealth, ANC, parity, residence, insurance

15.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 103: What each card must report before its output is usable

#	Model	Diagnostics and validation
67	Health insurance coverage	scheme-definition harmonization. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
68	Reported access barriers	question availability and scale checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
69	Provider choice for child illness	IIA/nesting tests. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
70	Facility delivery choice	IIA and sample checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

15.5 What the committed runs produced

No indicator table from this family is shipped in `08_Data/`. The cards that completed wrote coefficient tables and model cards rather than headline indicators; Appendix K carries every coefficient table the run produced.

15.6 What the surveys refused

Table 104: Verbatim, from the catalogue summaries

#	Model	Survey	Reason the run gave
67	Health insurance coverage	Kenya 2022 DHS	eligible sample 0 < disclosure threshold 25
68	Reported access barriers	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs a big-problem access-barrier cohort (v467b–v467f) — not yet built
69	Provider choice for child illness	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: needs a treatment-source (h32*) multinomial cohort — not yet built

15.7 Where this family goes

The demand side of facility planning (H-A-06 Huff choice) and the out-of-pocket module of the poverty microsimulation (H-P-01).

Table 105: Each card's declared integration target

#	Model	Integration target
67	Health insurance coverage	UHC and financing module. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
68	Reported access barriers	transport/finance integration. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
69	Provider choice for child illness	public-private service demand. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
70	Facility delivery choice	maternal facility demand. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

15.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

> **THE RULE THAT APPLIES TO EVERY CARD IN PART II**
>
> Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

16. L. Inequality, Decomposition and Causal Policy Analysis

Table 106: Inequality, Decomposition and Causal Policy Analysis: the family at a glance

Cards in the family	**8**
Completed on Uganda 2016 DHS (UG2016DHS)	6
Completed on Kenya 2022 DHS (KE2022DHS)	6
Implemented in	`src/Models/inequality_causal/` — 8 Julia files
Downstream	Equity analysis, the concentration index of out-of-pocket payments (H-P-07), and the distributional inputs to CDCGE.

16.1 What this family estimates

Concentration and Erreygers indices, Wagstaff decomposition, Oaxaca-Blinder and Fairlie, propensity-score and instrumental variable estimation, and difference-in-differences across rounds.

Every other family answers 'how much'. This one answers 'to whom', and it is the family that turns a national average into a distributional statement a minister can act on.

16.2 The trap

> **FAMILY L**
>
> Half this family is descriptive and half is causal. The registry declares which before estimation, and a causal card that fails its gate returns a refusal rather than a weaker estimate.

16.3 The models

All 8 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 107: Family L: the 8 model cards

#	Model	Outcome	Estimator	Ran	n
71	Concentration index for health outcome	socioeconomic inequality in y	survey-adjusted concentration index	yes	4,423
72	Erreygers corrected concentration index	inequality for bounded binary outcomes	corrected concentration index	yes	4,423
73	Wagstaff decomposition	contributions to health inequality	decomposition	yes	4,423
74	Oaxaca-Blinder health-gap decomposition	group gap in continuous outcome	weighted Oaxaca-Blinder	yes	4,423
75	Fairlie decomposition	group gap in binary outcome	weighted nonlinear decomposition	yes	4,423
76	Propensity-score treatment effect	effect of observable treatment/exposure	matching/IPW/doubly robust	yes	4,423
77	Instrumental-variable health model	causal effect where valid instrument exists	2SLS/control function	no	—
78	Difference-in-differences with repeated DHS	policy effect across rounds/areas	repeated-cross-section DiD	no	—

16.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 108: Specification and inputs

#	Model	Core specification	Key inputs
71	Concentration index for health outcome	C=2/μ·Cov(y_i,R_i)	health outcome, DHS wealth rank, weights
72	Erreygers corrected concentration index	E=4μ/(b-a)·C	binary health outcome and wealth rank
73	Wagstaff decomposition	C_y=Σ_k (β_k $\bar{x}$_k/μ)C_k + GC_ε/μ	regression covariates and wealth rank
74	Oaxaca-Blinder health-gap decomposition	Δ=Explained+Unexplained	e.g. HAZ/BMI by urban-rural or sex
75	Fairlie decomposition	ΔP=Composition+Structure	binary outcome by group
76	Propensity-score treatment effect	ATT=E[Y(1)-Y(0)|T=1]	DHS exposure plus rich confounders
77	Instrumental-variable health model	Y_i=βT_i+X_iγ+ε_i; T_i=πZ_i+X_iδ+ν_i	outcome, treatment, defensible external/DHS instrument
78	Difference-in-differences with repeated DHS	Y_{irt}=α+β(Treat_r$\times$Post_t)+δ_r+τ_t+Xγ+ε	harmonized repeated DHS plus policy timing

16.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 109: What each card must report before its output is usable

#	Model	Diagnostics and validation
71	Concentration index for health outcome	bounded-outcome correction sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
72	Erreygers corrected concentration index	ranking and bounds checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
73	Wagstaff decomposition	model dependence and residual share. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
74	Oaxaca-Blinder health-gap decomposition	reference-group sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
75	Fairlie decomposition	ordering/bootstrap sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
76	Propensity-score treatment effect	balance, overlap, sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
77	Instrumental-variable health model	first-stage strength, exclusion argument. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
78	Difference-in-differences with repeated DHS	parallel-trend evidence, composition checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

16.5 What the committed runs produced

Inequality measures

Table 110: Four indicators, Uganda 2016 DHS (UG2016DHS)

Indicator	Concentration index	Erreygers	SII	Direction
stunting	-0.1086	-0.1223	-0.1835	concentrated among the poor
facility delivery	0.0803	0.2358	0.3537	concentrated among the better off
modern contraception	0.1152	0.1603	0.2404	concentrated among the better off
zero dose	-0.0026	-0.0006	-0.0009	concentrated among the poor

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

The decomposition

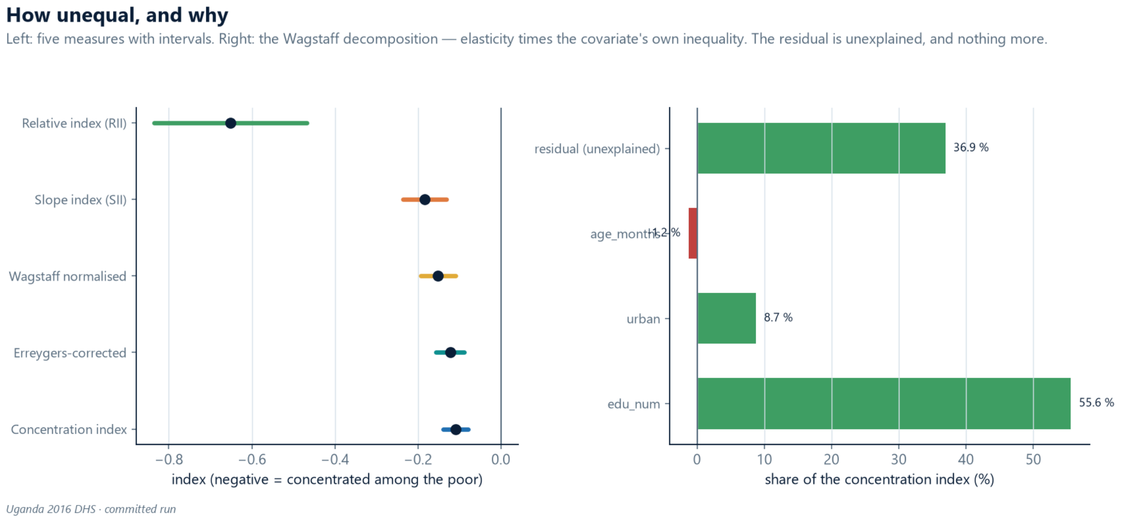
Table 111: Wagstaff decomposition of the stunting concentration index

Covariate	Elasticity	CI of covariate	Contribution	Share
edu_num	-0.3491	0.1728	-0.0603	55.6 %
urban	-0.0188	0.5044	-0.0095	8.7 %
age_months	0.1283	0.0102	0.0013	-1.2 %
residual (unexplained)	—	—	-0.0401	36.9 %

WHAT THE RESIDUAL IS NOT

It is not discrimination and it is not a causal residual. It absorbs different returns to the same covariate across groups, omitted variables and measurement error, in unknown proportions. Name it 'unexplained' every time it appears.

Figure 9: Five inequality measures for stunting, and the decomposition of the concentration index into covariate



Notes: contributions. Source: Uganda 2016 DHS · committed run.

16.6 What the surveys refused

Table 112: Verbatim, from the catalogue summaries

#	Model	Survey	Reason the run gave
77	Instrumental-variable health model	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: requires a credible instrument (identification review) — Causal.jl IV template refuses by default on standard DHS
78	Difference-in-differences with repeated DHS	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: requires harmonised repeated rounds + policy timing — available via Causal.jl DiD on pooled multi-round data, not a single-survey run

16.7 Where this family goes

Equity analysis, the concentration index of out-of-pocket payments (H-P-07), and the distributional inputs to CDCGE.

Table 113: Each card's declared integration target

#	Model	Integration target
71	Concentration index for health outcome	equity dashboard. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
72	Erreygers corrected concentration index	cross-country equity analysis. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
73	Wagstaff decomposition	policy prioritization. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
74	Oaxaca-Blinder health-gap decomposition	equity diagnostics. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
75	Fairlie decomposition	targeted equity policy. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
76	Propensity-score treatment effect	policy evaluation where identification is defensible. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
77	Instrumental-variable health model	only activated after identification review. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
78	Difference-in-differences with repeated DHS	evaluates reforms with geographic/time variation. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

16.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

> **THE RULE THAT APPLIES TO EVERY CARD IN PART II**
>
> Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

17. M. Multilevel, Spatial and Small-Area Models

Table 114: Multilevel, Spatial and Small-Area Models: the family at a glance

Cards in the family	**7**
Completed on Uganda 2016 DHS (UG2016DHS)	2
Completed on Kenya 2022 DHS (KE2022DHS)	2
Implemented in	`src/Models/multilevel_spatial/` — 7 Julia files
Downstream	Sub-national targeting and the geographic layer the accessibility and optimisation models run over.

17.1 What this family estimates

Cluster and region random effects, spatial Gaussian processes, Fay-Herriot and unit-level small-area estimation, spatially varying coefficients, and cluster accessibility.

A national estimate is not a plan. A district estimate is — but a survey powered for regions will not give you one directly. This family borrows strength, and says how much it borrowed.

17.2 The trap

FAMILY M

Every spatially explicit card depends on cluster coordinates that were deliberately displaced. Buffer extraction is the rule, and no coordinate leaves the system.

17.3 The models

All 7 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 115: Family M: the 7 model cards

#	Model	Outcome	Estimator	Ran	n
79	Cluster random-intercept health model	health outcome with community heterogeneity	multilevel GLMM	yes	4,423
80	Region/district hierarchical model	outcome with higher-level heterogeneity	hierarchical model	yes	4,423
81	Spatial Gaussian process prevalence model	continuous spatial risk surface	Bayesian geostatistical model	no	—
82	Bayesian small-area prevalence	area prevalence borrowing strength	area-level Bayesian SAE	no	—
83	Unit-level small-area model	individual DHS outcome plus census covariates	unit-level SAE	no	—
84	Spatially varying coefficient model	effect heterogeneity over space	Bayesian spatial varying coefficients	no	—
85	DHS cluster accessibility-health model	health outcome linked to modeled facility travel time	survey/multilevel regression	no	—

17.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 116: Specification and inputs

#	Model	Core specification	Key inputs
79	Cluster random-intercept health model	g(E[Y_ic])=X_icβ+u_c	individual/household variables and cluster ID
80	Region/district hierarchical model	g(E[Y_ij])=X_ijβ+u_j	DHS outcome, region/district
81	Spatial Gaussian process prevalence model	g(p(s))=X(s)β+w(s), w~GP(0,Cθ)	DHS cluster prevalence, GPS, covariates
82	Bayesian small-area prevalence	logit(p_j)=X_jβ+u_j+v_j	DHS direct estimates plus auxiliary area covariates
83	Unit-level small-area model	g(E[Y_ij])=X_ijβ+u_j	DHS microdata + harmonized census/ satellite covariates
84	Spatially varying coefficient model	g(p(s))=β_0(s)+Σ_kβ_k(s)X_k	DHS GPS and covariates
85	DHS cluster accessibility-health model	Pr(Y_i=1)=F(βT_c+X_iγ)	DHS GPS cluster, travel-time surface, health outcome

17.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 117: What each card must report before its output is usable

#	Model	Diagnostics and validation
79	Cluster random-intercept health model	ICC, random-effect distribution. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
80	Region/district hierarchical model	variance partition and shrinkage checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
81	Spatial Gaussian process prevalence model	spatial CV, variogram/range checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
82	Bayesian small-area prevalence	posterior predictive checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
83	Unit-level small-area model	out-of-sample area validation. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
84	Spatially varying coefficient model	spatial CV and complexity checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
85	DHS cluster accessibility-health model	GPS displacement sensitivity buffers. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

17.5 What the committed runs produced

Small-area estimates and their shrinkage

Table 118: Fay–Herriot small-area estimates for stunting, Uganda 2016 DHS (UG2016DHS) — all 15 sub-regions

Area	Direct	Direct SE	EBLUP	EBLUP SE	γ	Model share
bugisu	36.3 %	0.0421	34.1 %	0.0361	0.736	26 %
kigezi	29.1 %	0.0404	28.9 %	0.0350	0.752	25 %
busoga	26.9 %	0.0354	27.1 %	0.0316	0.797	20 %
west nile	34.3 %	0.0349	33.1 %	0.0313	0.802	20 %
karamoja	34.9 %	0.0341	33.6 %	0.0307	0.810	19 %
tooro	40.4 %	0.0317	38.3 %	0.0289	0.832	17 %
north buganda	27.0 %	0.0315	27.2 %	0.0288	0.833	17 %
ankole	29.2 %	0.0314	29.0 %	0.0287	0.834	17 %
acholi	30.7 %	0.0314	30.2 %	0.0287	0.834	17 %
bunyoro	35.8 %	0.0309	34.5 %	0.0283	0.838	16 %
kampala	17.6 %	0.0307	19.3 %	0.0281	0.840	16 %
bukedi	20.6 %	0.0277	21.6 %	0.0258	0.865	13 %
south buganda	25.8 %	0.0267	26.0 %	0.0249	0.874	13 %
lango	22.0 %	0.0214	22.5 %	0.0205	0.915	8 %
teso	13.0 %	0.0202	14.2 %	0.0194	0.924	8 %

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

The variance decomposition

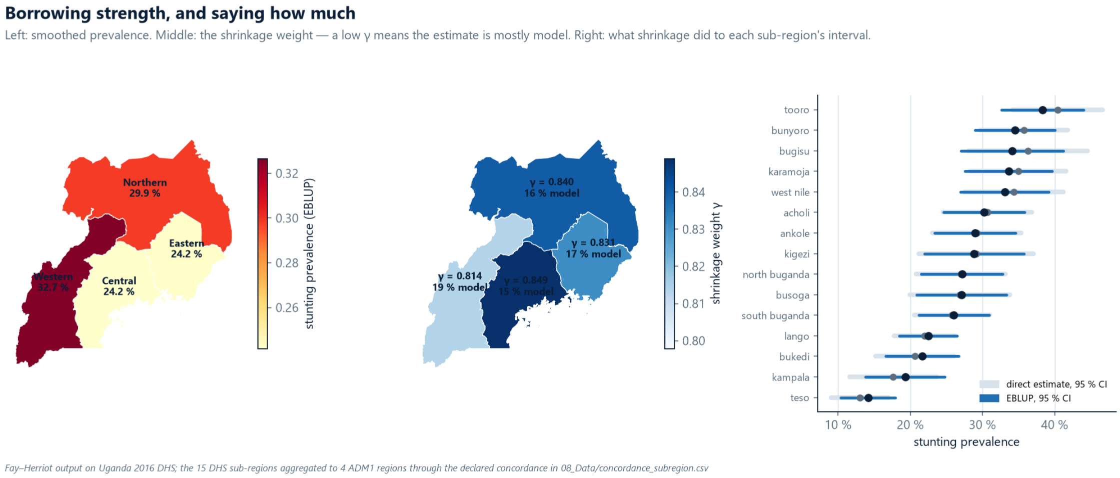
Table 119: Stunting cohort, Uganda 2016 DHS (UG2016DHS)

Quantity	Empty model	Full model	Reading
σ^2_u	0.4879	0.4983	between-cluster variance, log-odds scale
ICC	12.9 %	13.2 %	share of total variance that is between clusters
MOR	1.947	1.961	the median odds ratio between two random clusters
PCV	—	-2.1 %	the share of cluster variance the covariates explain
Clusters	690	690	PSUs in the cohort

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

> **HL-07 — A NEGATIVE PROPORTIONAL CHANGE IN VARIANCE**
>
> The full model's cluster variance (0.498) is slightly larger than the empty model's (0.488), so the PCV is -2.1 %. That is not a bug and it is not rounding. It means the compositional covariates in this specification do not account for why clusters differ. A model whose PCV is negative must not be described as explaining geographic variation.

Figure 10: Small-area stunting estimates by DHS sub-region, and the shrinkage weight that says how much of each number



Notes: is model rather than sample. Source: Fay–Herriot output, Uganda 2016 DHS; boundaries aggregated to ADM1 through a declared concordance.

17.6 What the surveys refused

Table 120: Verbatim, from the catalogue summaries

#	Model	Survey	Reason the run gave
81	Spatial Gaussian process prevalence model	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: requires Bayesian geostatistics (R-INLA/SPDE) — native BYM/CAR available via SpatialModels.jl + run_spatial_adjacency.jl
82	Bayesian small-area prevalence	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: area-level SAE is implemented via SmallAreaEstimation.jl (Fay-Herriot) + run_africa_sae_forecast.jl — operates on aggregated regional inputs, not a per-model unit run
83	Unit-level small-area model	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: requires harmonised census/satellite auxiliary covariates not present in this cache
84	Spatially varying coefficient model	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: requires Bayesian spatially-varying coefficients (R-INLA/SPDE) — not on this host
85	DHS cluster accessibility-health model	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: requires cluster travel-time (GE GPS + facility register) merged to the outcome cohort — travel time computed by run_gis_access.jl; merge-to-outcome not yet wired

17.7 Where this family goes

Sub-national targeting and the geographic layer the accessibility and optimisation models run over.

Table 121: Each card's declared integration target

#	Model	Integration target
79	Cluster random-intercept health model	community-level targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
80	Region/district hierarchical model	subnational planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
81	Spatial Gaussian process prevalence model	GIS health intelligence. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
82	Bayesian small-area prevalence	fills local planning gaps. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
83	Unit-level small-area model	continental health maps. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
84	Spatially varying coefficient model	locally tailored interventions. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
85	DHS cluster accessibility-health model	transport-health investment bridge. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

17.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

> **THE RULE THAT APPLIES TO EVERY CARD IN PART II**
>
> Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

18. N. Prediction, Microsimulation and Bridge Models

Table 122: Prediction, Microsimulation and Bridge Models: the family at a glance

Cards in the family	**12**
Completed on Uganda 2016 DHS (UG2016DHS)	5
Completed on Kenya 2022 DHS (KE2022DHS)	5
Implemented in	`src/Models/prediction_bridge/` — 12 Julia files
Downstream	Every downstream EDIS module. This family is the handover.

18.1 What this family estimates

Tree ensembles and stacked learners, a vulnerability index, household and intervention microsimulation, and the bridges to climate, agriculture, education, labour productivity and the household CGE.

This family is the boundary of the estate. It contains the prediction models, the microsimulation and every bridge to another EDIS sector — and it is the family where the honest answer is most often that the data will not support the question.

18.2 The trap

> **FAMILY N**
>
> This is the sparsest family on both surveys, because most of its cards need a second data source — climate rasters, agricultural exposure, a facility register — that a household survey does not contain.

18.3 The models

All 12 cards, as specified. The outcome and estimator columns are the specification's own words; the status column is what the committed run on Uganda 2016 DHS did with the card.

Table 123: Family N: the 12 model cards

#	Model	Outcome	Estimator	Ran	n
86	Random-forest health-risk model	predict selected DHS health outcome	survey-aware resampling/weighted RF where feasible	no	—
87	Gradient-boosted health-risk model	predict selected outcome	XGBoost/LightGBM/CatBoost equivalent	no	—
88	Super learner/stacked ensemble	combine candidate predictive models	cross-validated stacking	no	—
89	DHS health vulnerability index	multidimensional household/individual vulnerability	PCA/factor or transparent normative weights	yes	19,588
90	Household health microsimulation	simulate policy-induced probability changes	static probabilistic microsimulation	yes	4,423
91	Maternal-child intervention microsimulation	jointly simulate ANC/SBA/PNC and child outcomes	sequential microsimulation	no	—
92	Climate-health DHS bridge	translate climate exposures into health-risk shifts	multilevel/spatial regression then scenario transfer	no	—
93	Agriculture-nutrition DHS bridge	translate food/agricultural shocks into nutrition outcomes	regression/microsimulation bridge	no	—
94	Education-health DHS bridge	estimate health returns to maternal/household education	survey regression/causal option where justified	yes	4,423
95	Health-to-labour productivity bridge	map DHS morbidity/nutrition states to productivity parameters	bridge calibration with sensitivity ranges	no	—
96	Health-to-household/CGE bridge	map health indicators to representative households/factors	weighted aggregation and crosswalk	yes	4,423
97	Health policy targeting score	rank households/areas by expected benefit or risk	decision rule/optimization-ready score	yes	4,423

18.3.1 Specifications

The formal specification of each card, from the technical manual. Where two cards share a specification they differ in cohort, not in estimator — and the cohort is the model.

Table 124: Specification and inputs

#	Model	Core specification	Key inputs
86	Random-forest health-risk model	$\hat{Y}$_i=RF(X_i)	harmonized DHS predictors
87	Gradient-boosted health-risk model	$\hat{Y}$_i=Σ_m η f_m(X_i)	DHS predictors
88	Super learner/stacked ensemble	$\hat{Y}$_i=Σ_m α_m $\hat{Y}$_{im}, α_m$\geq$0	predictions from validated base learners
89	DHS health vulnerability index	V_i=Σ_k ω_k z_{ik}	nutrition, morbidity, WASH, wealth, maternal care, demographics
90	Household health microsimulation	Y_i^{s}~Bernoulli(p_i^{s}), logit(p_i^{s})=X_i^{s}β	estimated DHS model coefficients and scenario shocks
91	Maternal-child intervention microsimulation	p_{ki}^{s}=F(X_{ki}^{s}β_k)	linked estimated model cards
92	Climate-health DHS bridge	Δlogit(p_i)=β_C ΔClimate_c	DHS health outcome + externally matched climate exposure
93	Agriculture-nutrition DHS bridge	ΔY_i=β_F ΔFoodSecurity_i + . . .	DHS nutrition plus food/agriculture exposure proxies
94	Education-health DHS bridge	g(E[Y_i])=β_E Edu_i+X_iγ	DHS education and health outcomes
95	Health-to-labour productivity bridge	Prod_f^s=Prod_f^0(1+φ_f ΔHealth_f)	DHS health prevalence by working-age group plus literature/linked earnings evidence
96	Health-to-household/CGE bridge	H_{h,f}=Σ_i w_i 1(i$\in$h,f)Y_i / Σ_i w_i1(i$\in$h,f)	DHS outcomes, household/skill/geography crosswalks
97	Health policy targeting score	Score_i=E[Benefit_i|X_i]-λCost_i	validated DHS risk models and policy eligibility

18.4 Survey design and required diagnostics

THE SURVEY-DESIGN TREATMENT EVERY CARD IN THIS FAMILY DECLARES

Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.

Table 125: What each card must report before its output is usable

#	Model	Diagnostics and validation
86	Random-forest health-risk model	nested CV, calibration, subgroup performance. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
87	Gradient-boosted health-risk model	nested CV, calibration, SHAP stability. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
88	Super learner/stacked ensemble	out-of-fold performance. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
89	DHS health vulnerability index	weight sensitivity and construct validity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
90	Household health microsimulation	zero-shock reproduction, Monte Carlo error. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
91	Maternal-child intervention microsimulation	pathway consistency and uncertainty propagation. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
92	Climate-health DHS bridge	exposure-window and GPS displacement sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
93	Agriculture-nutrition DHS bridge	mediation and external-variable caveats. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
94	Education-health DHS bridge	confounding sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
95	Health-to-labour productivity bridge	unit consistency and scenario sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
96	Health-to-household/CGE bridge	share reconciliation and coverage. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks
97	Health policy targeting score	fairness, calibration, threshold sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks

18.5 What the committed runs produced

Prediction performance, on cluster-held-out folds

Table 126: Child stunting risk, Uganda 2016 DHS (UG2016DHS)

Model	AUROC	AUPRC	Brier	Log loss	Calibration slope	Prevalence
logistic	0.586	0.335	0.199	0.586	0.863	28.4 %
random_forest	0.542	0.327	0.264	1.984	0.026	28.4 %

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

Table 127: Zero-dose child risk, Uganda 2016 DHS (UG2016DHS)

Model	AUROC	AUPRC	Brier	Log loss	Calibration slope	Prevalence
logistic	0.524	0.066	0.047	0.205	0.052	4.8 %
random_forest	0.502	0.064	0.048	0.538	0.001	4.8 %

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

HL-05 — THE HONEST CONCLUSION

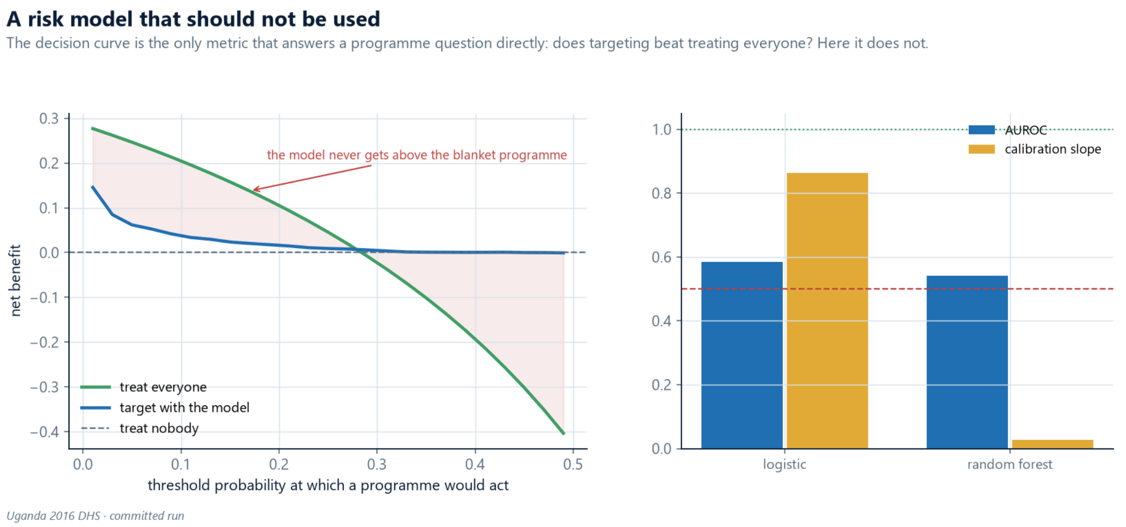
At every threshold examined, treating all children in the cohort has a higher net benefit than targeting with this model. The correct output is therefore not a risk score; it is the sentence *individual-level targeting for stunting is not supported by these covariates on this survey*. That saves a programme the cost of a targeting exercise that would perform worse than a blanket one — and the fairness audit shows the score would move resources away from the worst-affected groups. Area-level targeting, from Chapter 17, is what the same data does support.

The cross-sector bridges this family owns

Table 128: Chapter 32 works through every one, including the refusals

Link	Target module	Status	Rows
poverty_microsim	EDIS_Poverty_Microsimulation	exported	19,588
education	EDIS_Education	exported	15
macro_cdcge	EDIS_CDCGE	exported	15
energy	EDIS_Energy	exported	15
agriculture_food	EDIS_Agriculture	exported	180
transport	EDIS_Transport	skipped	0
climate	EDIS_Climate	skipped	0

Figure 11: The decision curve for the child stunting risk model



Notes: At every threshold examined a blanket programme has a higher net benefit than targeting — the finding registered as HL-04. Source: Uganda 2016 DHS · committed run.

Figure 12: The fairness audit

Notes: Predicted risk is far below observed prevalence in every group, and the gap is largest where prevalence is highest. Source: Uganda 2016 DHS · committed run.

ml stunting importance

Cluster-aware permutation importance: the drop in AUROC when a feature is shuffled. Importance is not effect.

Table 129: ml stunting importance, Uganda 2016 DHS (UG2016DHS)

feature	auroc drop
age_months	0.1020
wealth_q=5	0.0317
wealth_q=2	0.0299
residence=urban	0.0281
wealth_q=3	0.0248
education=none	0.0200
education=secondary	0.0186
wealth_q=4	0.0166
education=primary	0.0096

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

gb stunting importance

The same for the gradient-boosted model.

Table 130: gb stunting importance, Uganda 2016 DHS (UG2016DHS)

feature	importance	sd	baseline
age_months	0.1024	0.0079	0.6672
wealth_q=5	0.0110	0.0014	0.6672
wealth_q=4	0.0044	0.0015	0.6672
education=none	0.0038	0.0014	0.6672
education=primary	0.0029	0.0013	0.6672
wealth_q=2	0.0008	0.0003	0.6672
education=secondary	0.0006	0.0004	0.6672
wealth_q=3	0.0003	0.0010	0.6672
residence=urban	0.0000	0.0000	0.6672

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

18.6 What the surveys refused

Table 131: Verbatim, from the catalogue summaries

#	Model	Survey	Reason the run gave
86	Random-forest health-risk model	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: random-forest risk models run via Prediction.jl/ml_predict (grouped-CV AUROC/Brier/calibration) as a dedicated ML pipeline, not the design-based per-model engine
87	Gradient-boosted health-risk model	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: gradient boosting runs via Prediction.jl/gradient_boost with grouped-CV tuning + SHAP — dedicated ML pipeline
88	Super learner/stacked ensemble	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: cross-validated stacking of base learners — not yet wired (base learners available via Prediction.jl)
91	Maternal-child intervention microsimulation	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: sequential cascade microsimulation across linked cards — orchestrated via run_extended.jl scenarios, not a single-cohort run
92	Climate-health DHS bridge	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: requires cluster-matched climate exposure (CHIRPS/ temperature rasters) — blocked by the GDAL/SAC raster wall on this host
93	Agriculture-nutrition DHS bridge	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: requires food-security / agricultural exposure proxies not collected in standard DHS
95	Health-to-labour productivity bridge	Uganda 2016 DHS, Kenya 2022 DHS	not wired on this platform: calibration bridge to CDCGE factor productivity — implemented via CrossSectorExports.jl (health→macro), needs literature elasticities not a per-cohort fit

18.7 Where this family goes

Every downstream EDIS module. This family is the handover.

Table 132: Each card's declared integration target

#	Model	Integration target
86	Random-forest health-risk model	AI risk stratification. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
87	Gradient-boosted health-risk model	predictive layer for decision support. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
88	Super learner/stacked ensemble	robust predictive service. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
89	DHS health vulnerability index	cross-sector targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
90	Household health microsimulation	policy scenario engine. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
91	Maternal-child intervention microsimulation	health package comparison. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
92	Climate-health DHS bridge	EDIS climate module. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
93	Agriculture-nutrition DHS bridge	agriculture-health integration. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
94	Education-health DHS bridge	education-human-capital integration. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
95	Health-to-labour productivity bridge	CDCGE factor-productivity shocks. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
96	Health-to-household/CGE bridge	CDCGE distributional integration. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables
97	Health policy targeting score	feeds EDIS resource-allocation optimization. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables

18.7.1 Policy scenarios this family supports

Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.

THE RULE THAT APPLIES TO EVERY CARD IN PART II

Simulating a change in a modifiable determinant while holding non-policy covariates fixed is legitimate and useful. Labelling the result an effect is not, unless the causal module produced it and its gate passed. Chapter 16 covers the gate; Chapter 36 covers the wording.

Part III — The health-system engine

Demography, epidemiology, service demand, facility capacity, workforce and supply chain — the chain that turns a population into a procurement bill.

Part II estimated what is happening to people. Part III turns that into what a health system has to do about it. The engine runs as a sequence, and the sequence matters: an error in the base-year age structure is an error in the medicine order five chapters later.

EVERYTHING IN PARTS III AND IV IS SYNTHETIC (HL-02)

The engine has been run end to end on Zandia (ZAN) — the health-system engine's SYNTHETIC demo country — 2,470,000 people, base year 2025, projection year 2035. Its population, facilities, workforce, financing and disease parameters are demo values. Every figure in these chapters demonstrates that the mechanics work and shows what the output looks like. None of it is evidence about a real country, and presenting it as such is on the automatic-fail list.

19. Sets, notation and the run

19.1 Sets and indices

Table 133: The index sets the whole engine runs over

Symbol	Set	Source table
$i \in I$	settlements and demand origins	`settlements`
$r \in R$	administrative areas	`admin_areas` (level 1)
$f \in F$	health facilities	`facilities`
$j \in J$	candidate facility sites	`candidate_sites`
$a \in A$	age groups {0–4, 5–14, 15–49, 50–64, 65+}	`population`
$x \in \{F,M\}$	sex	`population`
$d \in D$	diseases	`diseases`
$k \in K$	services	`services`
$c \in C$	workforce cadres	`cadres`
$m \in M$	medicines	`medicines`
$w \in W$	warehouses	`warehouses`
$h \in H$	households	`households`
$t \in T$	years, base year to projection year	configuration

Services K are OUTPATIENT, INPATIENT, MATERNAL, DELIVERY, IMMUNIZATION, SURGERY, LAB, EMERGENCY, CHRONIC, MENTAL and REHAB. Every disease maps to one of them, and that mapping is what turns epidemiology into service demand.

19.2 Time-varying parameters

EQ. H-0-01 TRAJECTORY INTERPOLATION

$$\text{param\_at}(p,t) = \begin{cases} v_1 & t \le t_1 \\ v_n + (v_{n+1}-v_n)(t-t_n)/(t_{n+1}-t_n) & t_n \le t \le t_{n+1} \\ v\_last & t \ge t\_last \end{cases}$$

any parameter may follow sorted waypoints; flat outside the range (8)

The parameters wired to trajectories are the policy levers: `coverage_target`, `seeking_rate`, `population_growth`, `shock_multiplier`, `vaccination_coverage`, `user_fee_removal`, `medicine_subsidy`, `oop_shock` and the per-cadre staffing inputs. A scenario in this engine is a set of waypoints, not a single number.

19.3 Discounting

EQ. H-0-02 DISCOUNTING

$$DF(t) = 1 / (1+\rho)^{(t - base\_year)}$$
$$D(L,\rho) = (1 - (1+\rho)^{(-L)}) / \ln(1+\rho)$$

DF discounts a cost; D is the present value of L annual life-years, used by the DALY calculation (9)

19.4 The run, and what it writes

Table 134: The committed health-system run this manual quotes

Field	Value
Run identifier	`run_ZAN_baseline_20260722175948`
Geography	ZAN
Scenario	baseline
Model version	0.3.0
Data version	demo-v1
Solver	HiGHS
Base year	2025
Projection year	2035

It writes nineteen output tables, from `population.csv` through `utilization.csv` and `workforce_gap.csv` to `outcomes.csv` and `underserved.csv`, plus a summary, an indicator table, an executive policy brief and an HTML report. Appendix L carries them in full.

20. Demography and epidemiology

Two blocks, and the first feeds the second. Neither is a forecast: both are projections under stated parameters, and the parameters are where the uncertainty lives.

20.1 Cohort-component projection

Table 135: The demography block, `Models/Population.jl`

ID	What it computes	Function
H-D-01	Survival & aging	
H-D-02	Fertility & births	
H-D-03	Migration	
H-D-04	Dependency ratio	

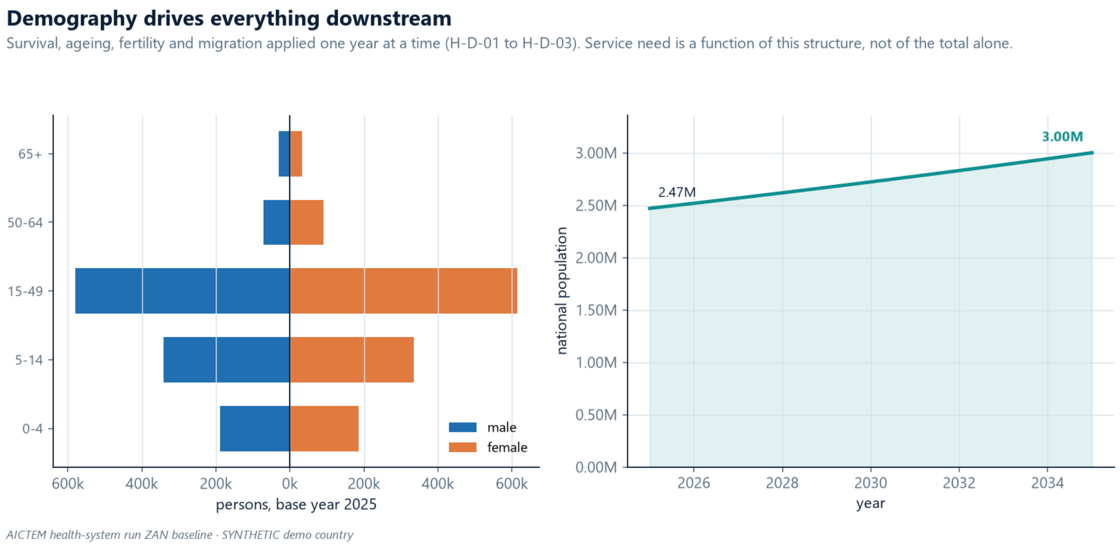
EQ. H-D-01 SURVIVAL AND AGEING

```
survivors[a,x] = POP[a,x] · clamp(σ_a + 0.004·urban_share,
                                   0.80, 0.9995)
aged_out = survivors[a,x] · ω_a , ω_a = 1/width_a
POP'[a,x] = (survivors − aged_out) + aged_out(from a−1)
σ_a is age-specific annual survival from the reference table; the oldest group retains its aged_out (10)
```

EQ. H-D-02 TO H-D-04 FERTILITY, MIGRATION, DEPENDENCY

```
births = POP[15-49, F] · (TFR/35)
                       · (param_at(population_growth,t)/0.025)
POP'[0-4, F] += births/(1+s) POP'[0-4, M] += births·s/(1+s)
POP'[a,x] ← POP'[a,x] · (1 + net_migration)
DR = 100 · (P0−4 + P5−14 + P65+) / (P15−49 + P50−64)
s = 1.03, the birth sex ratio; TFR is total fertility over the 15-49 band        (11)
```

Figure 13: Cohort-component population projection



Notes: the base-year age structure and the projection horizon. Source: EDIS health-system run ZAN baseline · SYNTHETIC demo country.

WHY THE AGE STRUCTURE AND NOT THE TOTAL

Service need is computed per age group, and the visits-per-case and staff-minutes parameters differ by service. Two countries with the same population and different age structures generate different outpatient loads, different delivery volumes and different workforce requirements. Projecting the total and applying a national rate throws that away.

20.2 The epidemiology block

Table 136: The epidemiology block, `Models/DiseaseBurden.jl`

ID	What it computes	Function
H-E-01	SIR	`sir_step`
H-E-02	SEIR	`seir_step`
H-E-03	Endemic (default engine)	
H-E-04	Climate multiplier	`climate_multiplier`
H-E-05	Prevention / vaccination	`prevention_factor`
H-E-06	Seasonal forcing	`seasonal_beta`
H-E-07	Effective reproduction number	`reproduction_number`
H-E-08	Age-structured SEIR	`simulate_age_seir`
H-E-09	Basic reproduction number	`basic_reproduction_number`
H-E-10	Population attributable fraction	`attributable_fraction`

20.2.1 The compartmental models

EQ. H-E-01, H-E-02 SIR AND SEIR

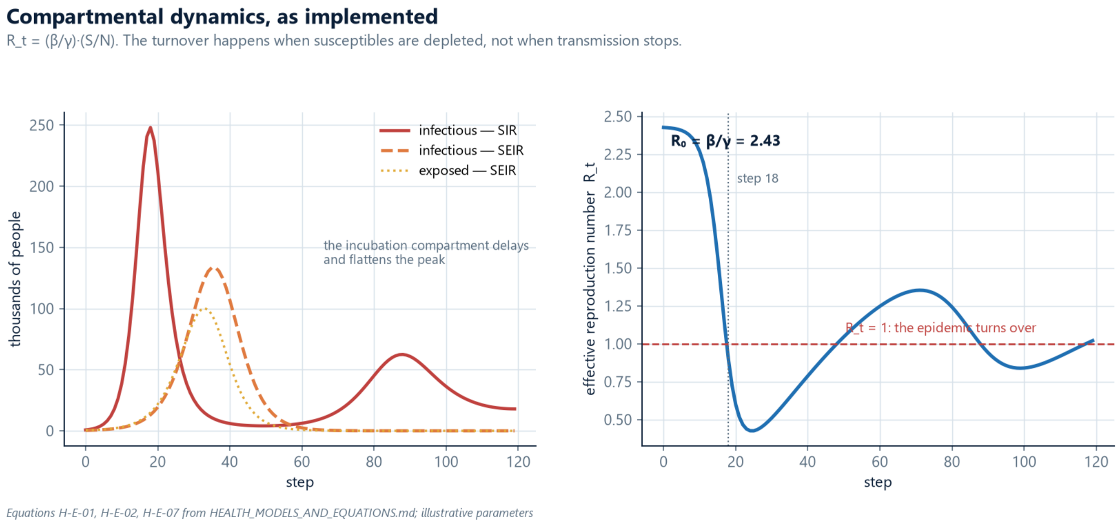
SIR newI = β S I / N , rec = γ I , d = μ I
S’ = S − newI (+0.02R waning)
I’ = I + newI − rec − d , R’ = R + rec (−0.02R)

SEIR infc = β S I/N , prog = σ E , rec = γ I , d = μ I
S’ = S−infc , E’ = E+infc−prog
I’ = I+prog−rec−d , R’ = R+rec
the closed-population identity S+I+R = N − d is asserted by the test suite (12)

EQ. H-E-06, H-E-07, H-E-09 REPRODUCTION AND SEASONALITY

R_0 = ρ(K), K[a,b] = $\beta\cdot$C[a,b]/γ next-generation matrix
R_t = (β/γ)$\cdot$(S/N) effective reproduction number
β(m) = β_0(1 + A$\cdot$cos(2π(m−m*)/12)) seasonal forcing
R_0 by power iteration on the next-generation matrix built from the WAIFW contact matrix (13)

Figure 14: SIR and SEIR trajectories and the effective reproduction number, computed from the documented step equations



Notes: H-E-01, H-E-02 and H-E-07. Source: Equations H-E-01, H-E-02, H-E-07 · illustrative parameters.

20.2.2 The endemic engine — the production path

EQ. H-E-03 TO H-E-05 ENDEMIC INCIDENCE, CLIMATE, PREVENTION

$$\mathrm{CASES}[r,d,t] = \mathrm{incidence}_0/1000 \cdot N[r,t] \cdot \mathrm{shock}(t) \cdot \mathrm{CM}(r,d) \cdot \mathrm{PF}(r,d,t)$$

$$\mathrm{PREV}[r,d,t] = \mathrm{prevalence}_0/1000 \cdot N[r,t] \cdot \mathrm{CM}(r,d) \cdot \mathrm{PF}(r,d,t)$$

$$\mathrm{DEATHS0} = \mathrm{CASES} \cdot \mathrm{CFR\_untreated}$$

$$\mathrm{CM}(r,d) = 1 + \mathrm{elasticity\_d} \cdot \Delta T \cdot \mathrm{malaria\_suitability}$$

$$\mathrm{PF}(r,d,t) = \mathrm{clamp}(1 - \mathrm{coverage\_v}(t)\cdot \mathrm{VE},\ 0.05,\ 1),\quad \mathrm{VE} = 0.8$$

CM is the climate multiplier (Chapter 29); PF is the prevention factor driven by vaccination coverage (14)

EQ. H-E-10 POPULATION ATTRIBUTABLE FRACTION

$$\mathrm{PAF} = p(\mathrm{RR} - 1) / (p(\mathrm{RR} - 1) + 1)$$

comparative risk assessment: the share of burden attributable to a risk factor with prevalence p and relative risk RR (15)

WHICH ENGINE PRODUCED THE NUMBER (HL-03)

`IMPLEMENTATION_STATUS.md` marks the compartmental models as implemented and tested against mass-balance identities, but not calibrated to the demo diseases. The endemic incidence engine is the default and it produced every case, prevalence and death figure quoted in this manual. A report that shows an epidemic curve must say which engine drew it.

20.3 What the run produced

Table 137: Disease burden, Zandia (ZAN) — the health-system engine's SYNTHETIC demo country

Disease	Deaths untreated	Deaths	Averted	DALYs
Malaria	75,717	24,229	51,487	1,892,928
NeonatalComp	47,462	17,086	30,375	1,695,083
Malnutrition	81,092	32,437	48,655	1,621,851
Injury	50,105	22,046	28,059	1,002,112
MaternalComp	20,650	6,112	14,538	743,421
Pneumonia	86,748	34,699	52,049	722,905
Diarrhoea	32,838	11,822	21,016	410,486
Depression	2,781	1,446	1,335	333,766
Hypertension	5,838	2,335	3,503	262,743
Tuberculosis	14,488	4,636	9,852	202,842
HIV	5,519	1,545	3,974	196,255
Diabetes	4,075	1,793	2,282	190,183

Notes: Source: Zandia (ZAN), committed run.

21. Service demand

Three words that a health ministry uses interchangeably and this engine does not: need, demand and utilisation. Need is epidemiological. Demand is behavioural. Utilisation is what capacity allowed. The engine computes all three and reports them separately, and Chapter 36 insists that a report says which one it is quoting.

Table 138: The service-demand block

ID	What it computes	Function
H-S-01	Need	
H-S-02	Adjusted demand	
H-S-03	Price elasticity of demand	`demand_price_factor`

EQ. H-S-01, H-S-02 NEED AND ADJUSTED DEMAND

```
NEED[r,k,t] = Σ_{d→k} CASES[r,d,t] · υ_k
DEMAND[r,k,t] = NEED[r,k,t] · seeking(t) · coverage(t)
                            · PriceFactor(t)
υ_k is visits per case for service k; seeking and coverage are trajectories        (16)
```

EQ. H-S-03 PRICE ELASTICITY OF DEMAND

```
PriceFactor(t) = (1 + fee(t)·ε) · (1 + 0.5·sub(t)·ε)
                              · shock_oop(t)^(−ε)
ε = 0.18 fee = user_fee_removal sub = medicine_subsidy
the elasticity is a configuration parameter, not an estimate from these data      (17)
```

21.1 What the run produced

Table 139: Need against demand by service, Zandia (ZAN) — the health-system engine's SYNTHETIC demo country

Service	Need	Demand	Demand / need
outpatient	17,418,721	9,057,735	0.520
chronic	2,342,815	1,218,264	0.520
inpatient	2,123,843	1,104,398	0.520
mental	1,112,553	578,527	0.520
emergency	911,011	473,725	0.520
delivery	413,011	214,766	0.520

Notes: Source: Zandia (ZAN), committed run.

THE RATIO IN THE LAST COLUMN IS A POLICY STATEMENT

It is the product of care-seeking, coverage and the price factor — three behavioural parameters. A ratio far below one does not mean people are healthy; it means they are not coming. That is a different problem from a capacity shortage, and it has different remedies.

22. Facility capacity, utilisation and queueing

A facility register says how many beds and how many consultation rooms exist. It does not say how many contacts they can deliver. The difference is staffing, readiness and opening hours, and it is where most unmet demand comes from.

Table 140: The capacity block, `Models/FacilityCapacity.jl`

ID	What it computes	Function
H-C-01	Staffing capacity	
H-C-02	Effective capacity	
H-C-03	Utilization / served / unmet	
H-C-04	Queueing wait probability	
H-C-05	Bed occupancy	`bed_occupancy`

EQ. H-C-01, H-C-02 STAFFING AND EFFECTIVE CAPACITY

```
STAFFCAP_f = Σ_c workers[f,c] · productivity_c
                              · (1 − absent_c) · μ_c(base_year)
share[f,k] = nominal[f,k] / Σ_k nominal[f,k]
CAP[f,k] = min( nominal[f,k],
                 max(STAFFCAP_f·share[f,k],
                     0.3·nominal[f,k]) )
             · readiness_f · (0.5 + 0.5·hours_f/24)
the 0.3 floor prevents a facility with no staff record collapsing to zero capacity       (18)
```

EQ. H-C-03 UTILISATION, SERVED AND UNMET

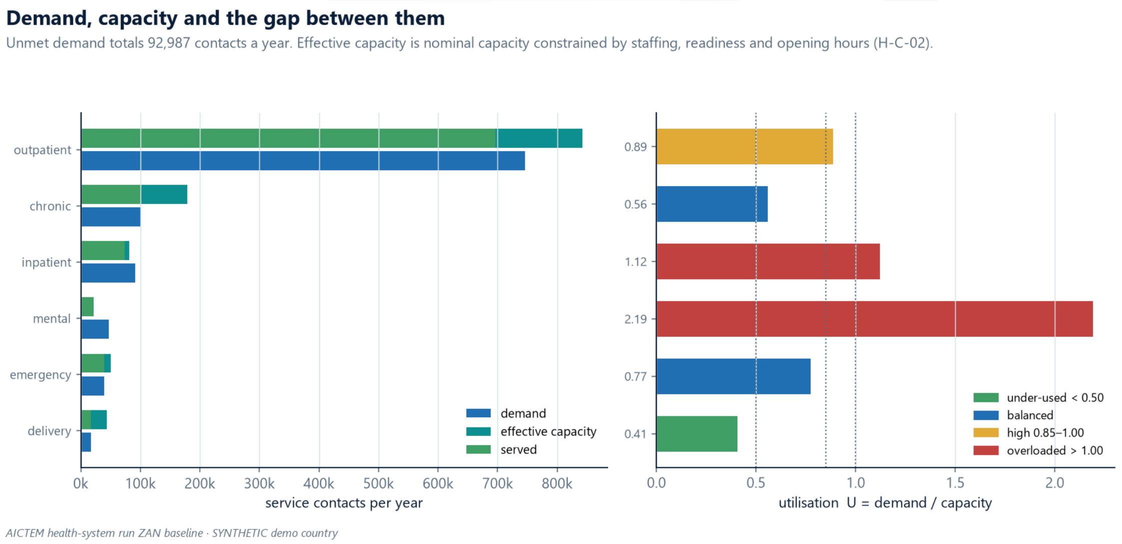
```
U[r,k] = DEMAND / CAP
SERVED = min(DEMAND, CAP)
UNMET = max(0, DEMAND − SERVED)
pressure:  under_used < 0.5 ≤ balanced < 0.85 ≤ high ≤ 1.0 < overloaded        (19)
```

EQ. H-C-04, H-C-05 ERLANG-C WAITING AND BED OCCUPANCY

```
c = ⌈CAP/APS⌉ , a = DEMAND/APS , APS = 4000 contacts/server-yr
P_wait = C(c,a) = B / (1 − (a/c)(1 − B))
Occ_f = admissions_f · LOS / (beds_f · 365)
B is the Erlang-B recursion; occupancy above 0.85 is flagged        (20)
```

22.1 What the run produced

Figure 15: Service demand against effective capacity, and the resulting utilisation pressure by service



Notes: Source: EDIS health-system run ZAN baseline · SYNTHETIC demo country.

Table 141: Capacity and utilisation by service, Zandia (ZAN) — the health-system engine's SYNTHETIC demo country

Service	Demand	Effective capacity	Served	Unmet	Utilisation	Pressure
outpatient	745,893	842,449	695,936	49,957	0.89	high
chronic	100,253	179,359	100,253	0	0.56	balanced
inpatient	90,935	81,140	73,778	17,156	1.12	overloaded
mental	47,612	21,740	21,740	25,872	2.19	overloaded
emergency	38,986	50,360	38,986	0	0.77	balanced
delivery	17,685	43,487	17,685	0	0.41	under-used

Notes: Source: Zandia (ZAN), committed run.

WHERE UNMET DEMAND ACTUALLY COMES FROM

Read the demand and effective-capacity columns together. A service can be overloaded while the register shows ample nominal capacity, because staffing, readiness or opening hours constrained it. Planning against the register — which is what a facility count does — will predict a surplus that does not exist.

23. Health workforce

The workforce requirement is derived from service demand, which means every assumption in Chapters 20 and 21 is inherited here. A workforce plan is only as good as the demand estimate behind it, and the sensitivity analysis in Chapter 27 is where that shows.

Table 142: The workforce block, `Models/WorkforcePlanning.jl`

ID	What it computes	Function
H-W-01	WISN requirement	
H-W-02	Staffing input & stock	`cadre_multiplier`
H-W-03	Stock-flow projection	`project_workforce`
H-W-04	Gap & density	
H-W-05	Training pipeline	`training_pipeline`
H-W-06	Skill mix	

EQ. H-W-01 WISN REQUIREMENT

```
AWT_c = hours_c · 60 · (1 − absent_c) available working minutes
NEED[c,r] = α · Σ_k DEMAND[r,k] · σ_k · ψ_{c,k} / AWT_c
α = 1.15 allowance ; σ_k service staff-minutes ;
ψ_{c,k} cadre-service mix
the Workload Indicators of Staffing Need method, as WHO specifies it    (21)
```

EQ. H-W-03, H-W-04 STOCK-FLOW, GAP AND DENSITY

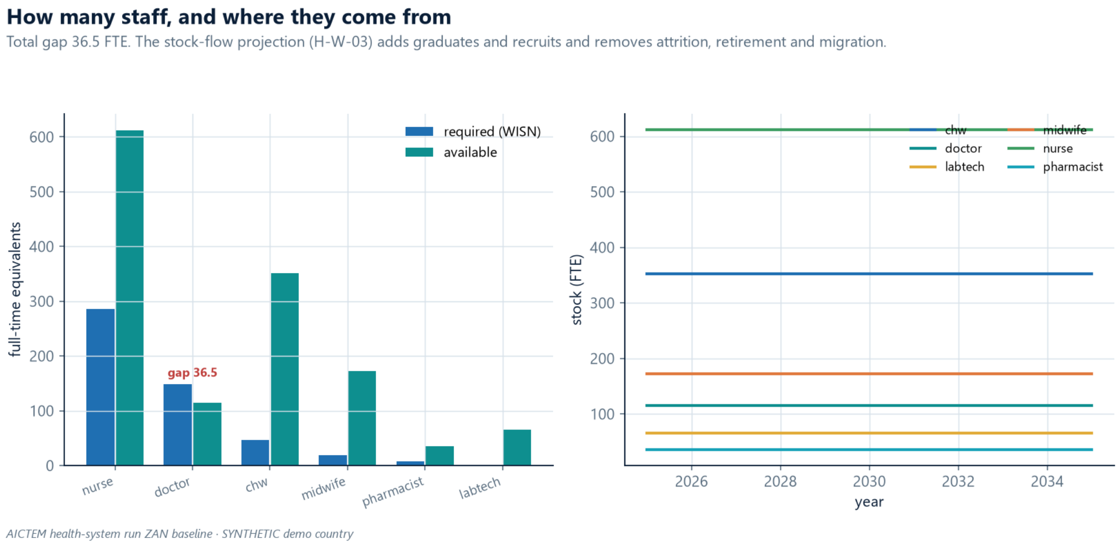
```
loss_c = attrition_c + retirement_c + migration_c
STOCK[c,t+1] = STOCK[c,t] + graduates_c + recruits_c
                         − loss_c · STOCK[c,t]
GAP[c,r] = max(0, NEED − AVAIL)
density = AVAIL / POP · 10^4                                            (22)
```

EQ. H-W-05 TRAINING PIPELINE

```
graduates = admissions · p p = 0.85
deployed = graduates · 0.95 · 0.90
admissions = STOCK · loss / (p · 0.95 · 0.90) to replace losses
stage pass rates:  examination 0.85, internship 0.95, deployment 0.90   (23)
```

23.1 What the run produced

Figure 16: Health workforce requirement against availability by cadre (WISN, H-W-01), and the stock-flow projection



Notes: Source: EDIS health-system run ZAN baseline · SYNTHETIC demo country.

Table 143: Workforce requirement against availability, Zandia (ZAN) — the health-system engine's SYNTHETIC demo country

Cadre	Required FTE	Available FTE	Gap	Density per 10,000
nurse	286.4	612.0	0.0	2.46
doctor	149.2	115.0	36.5	0.46
chw	46.1	352.0	0.0	1.45
midwife	18.4	173.0	0.0	0.70
pharmacist	7.8	36.0	0.0	0.14
labtech	0.0	66.0	0.0	0.27

Notes: Source: Zandia (ZAN), committed run.

A GAP IS NOT A VACANCY

The WISN requirement is what the modelled demand implies, under the staff-minute and cadre-mix parameters in the configuration. A vacancy is an unfilled established post. The two answer different questions and a ministry will have both numbers; say which one you are quoting.

24. Medicine supply chain

Demand is estimated as though supply were unconstrained. The supply-chain block is where that assumption is tested, and a stock-out is a service failure the demand model never sees.

Table 144: The supply-chain block, `Models/SupplyChainModel.jl`

ID	What it computes	Function
H-SC-01	Inventory balance	`stock_projection`
H-SC-02	Service-level safety stock	`safety_stock`
H-SC-03	EOQ	`eoq`
H-SC-04	s,S) policy	
H-SC-05	Commodity requirement	`commodity_requirement`

EQ. H-SC-01, H-SC-05 INVENTORY BALANCE AND COMMODITY REQUIREMENT

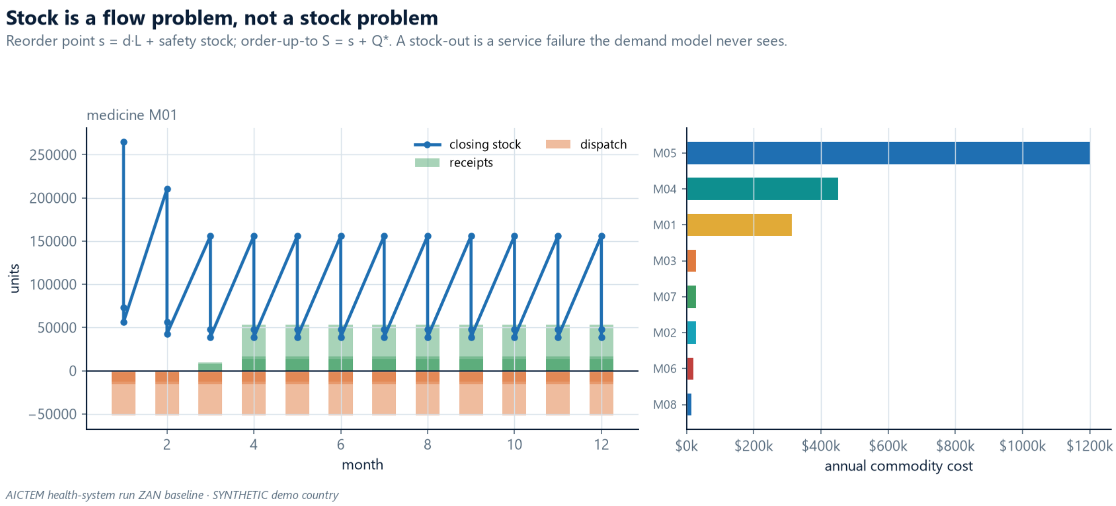
```
STOCK_t = STOCK_{t−1} + RECEIPTS − DISPATCH − LOSSES
LOSSES = opening · loss_rate
UNITS_m = Σ_k DEMAND_k · intensity_{m,k}                                  (24)
```

EQ. H-SC-02 TO H-SC-04 SAFETY STOCK, EOQ AND (s,S)

```
σ_d = cv · d
σ_LT = √( L·σ_d² + (d·cv_lead·L)² )
SS = z · σ_LT , z = Φ⁻¹(service_level)
Q* = √( 2·D·S_o / h ) EOQ
s = d·L + SS reorder point
S = s + Q* order-up-to
order = max(0, S − on_hand) when on_hand ≤ s
the service level sets z through the normal quantile; months of stock = STOCK / dispatch (25)
```

24.1 What the run produced

Figure 17: Inventory under an (s,S) policy



Notes: the sawtooth of receipts, dispatch and losses, with the reorder point and stock-outs. Source: EDIS health-system run ZAN baseline · SYNTHETIC demo country.

Table 145: Commodity requirement, Zandia (ZAN) — the health-system engine's SYNTHETIC demo country — the fourteen

Medicine	Units required	Cost
M05	10,025	$1.2M
M04	10,025	$451k
M01	261,062	$313k
M03	360,170	$29k
M07	401,012	$28k
M02	186,473	$28k
M06	401,012	$20k
M08	39,409	$14k

Notes: costliest lines Source: Zandia (ZAN), committed run.

The projection covers 240 warehouse-medicine-months and reports 0 stock-out months. Every one of them is a month in which the demand model's served quantity was unattainable, and the utilisation table does not know it.

THE ORDER THE PARAMETERS MATTER IN

Service level sets the safety stock, and safety stock is the expensive part. Moving from 90 to 99 per cent service level more than doubles z, and the holding cost follows. That is a policy choice about how often a facility may run out, and it belongs to a minister rather than to a modeller.

Part IV — Geography, optimisation and value

Where people are, where the facilities are, where the next ones should go, what it costs and what it buys.

25. Geographic accessibility

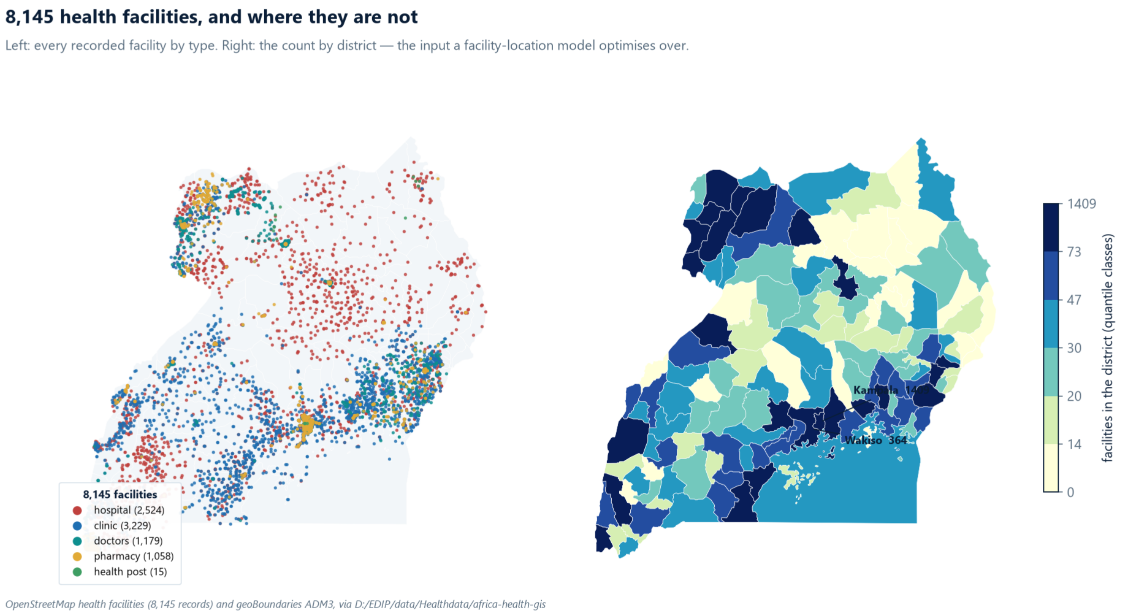
Everything so far has been aspatial: a national demand estimate, a national workforce gap. A ministry does not build a national clinic. This chapter is where the estate becomes geographic, and it is the point at which the survey stops being the main data source.

25.1 What accessibility runs on

Table 146: None of these is a household survey, and none is displaced

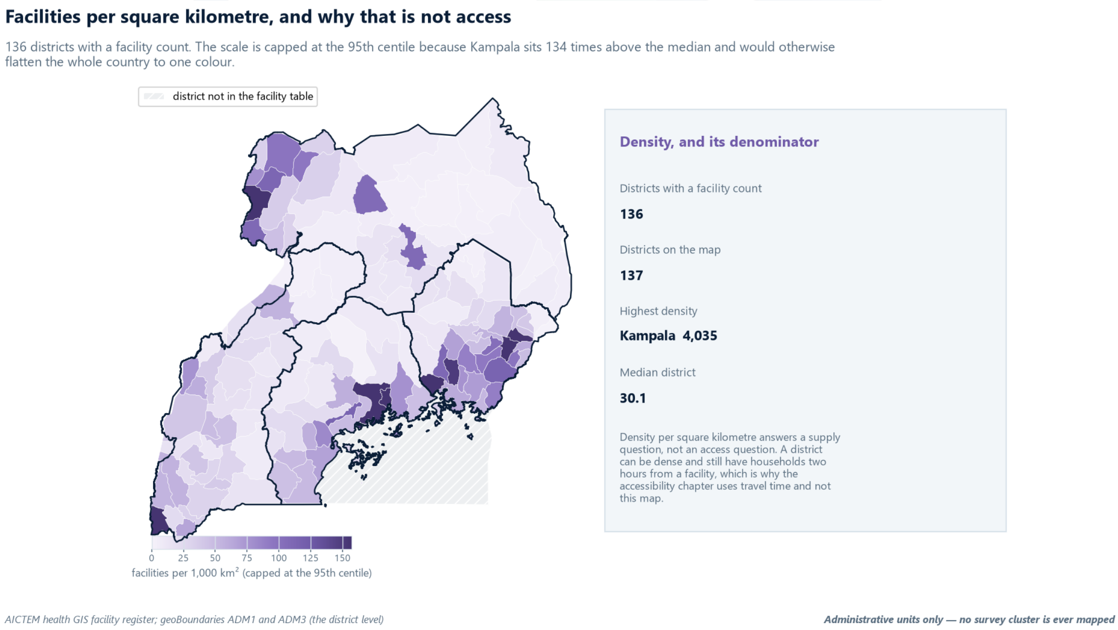
Layer	What it supplies	Source in this course
Facility register	the supply points and their capacity	OpenStreetMap — 54 African countries
Administrative boundaries	the areas estimates report to	geoBoundaries ADM0–ADM5 — 54 countries
Population grid	demand origins and catchment populations	WorldPop UN-adjusted — 54 countries
Road network	travel time between origin and facility	OpenStreetMap / Geofabrik — 54 countries

Figure 18: Every health facility OpenStreetMap records in Uganda, over the district boundaries



Notes: This is a facility register, not a survey — and it is what an accessibility model needs. Source: OpenStreetMap health facilities and geoBoundaries ADM3, D:/EDIP/data/Healthdata/africa-health-gis.

Figure 19: Facility density by district — facilities per 1,000 km^2



Notes: Density is not access: a dense district with poor roads can be less accessible than a sparse one. Source: OpenStreetMap and geoBoundaries ADM3.

25.2 Distance, travel time and the routing caveat

Table 147: The accessibility block, `GIS/Accessibility.jl`

ID	What it computes	Function
H-A-01	Distance & travel time	
H-A-02	Threshold coverage	
H-A-03	Gravity accessibility	
H-A-04	Enhanced 2SFCA	`compute_2sfca`
H-A-05	Three-step FCA	`compute_3sfca`
H-A-06	Huff choice probability	`huff_probabilities`
H-A-07	Underserved gap score	`identify_underserved_areas`
H-A-08	Access inequality	

EQ. H-A-01 DISTANCE AND TRAVEL TIME

```
haversine_km(o, f) great-circle distance
T = 60 · km / speed · seasonal_penalty Euclidean minutes
road network:  Floyd-Warshall shortest path on edge minutes
               (× 2.5 where seasonally impassable)
OD_{if} = min(network, Euclidean)
cached, and invalidated when an input changes                    (26)
```

HL-04 — SAY WHICH TRAVEL TIMES ARE ROUTED

Full OpenStreetMap routing is documented and the loader hooks exist, but the shipped implementation is a node graph with a great-circle fallback. Where the network is absent, `OD` is the Euclidean time and it is optimistic — real journeys are longer than straight lines. A travel-time map must state the share of origin-destination pairs that were routed.

25.3 The measures, from crudest to most defensible

EQ. H-A-02, H-A-03 THRESHOLD COVERAGE AND GRAVITY ACCESS

```
COV(τ) = Σ_i P_i·1[T_i ≤ τ] / Σ_i P_i τ ∈ {30,60,90,120}
ACCESS_i = Σ_f CAP_f / (1 + T_{if})^β gravity                     (27)
```

EQ. H-A-04 ENHANCED TWO-STAGE FLOATING CATCHMENT

```
g(T) = e^{−β T/τ} for T ≤ τ
Step 1 R_j = CAP_j / Σ_i g(T_{ij})·P_i supply ratio
Step 2 A_i = Σ_j g(T_{ij})·R_j accessibility
the measure to prefer when capacity matters                       (28)
```

EQ. H-A-05, H-A-06 THREE-STEP FCA AND HUFF CHOICE

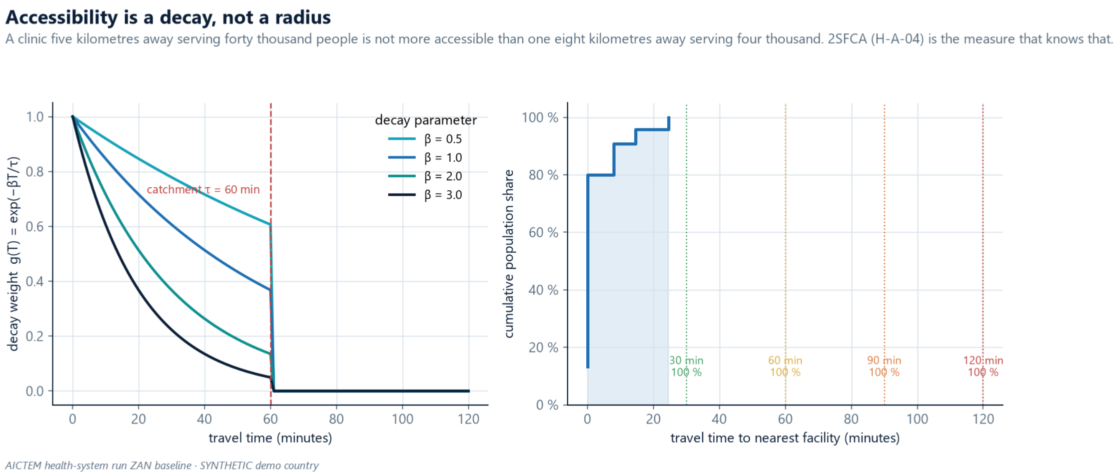
```
G_{ij} = g(T_{ij}) / Σ_k g(T_{ik}) selection weight
R_j = CAP_j / Σ_i G_{ij}·g(T_{ij})·P_i
A_i = Σ_j G_{ij}·g(T_{ij})·R_j
P(i→f) = [CAP_f/(1+T_{if})^β] / Σ_g [CAP_g/(1+T_{ig})^β]
```

```
Huff supplies the provider-choice probabilities family K estimates from the survey      (29)
```

EQ. H-A-07, H-A-08 UNDERSERVED GAP AND ACCESS INEQUALITY

```
G_i = T_i/τ + (1 − A_i/median(A))
underserved if T_i > τ or A_i < 0.5·median(A)
Theil = Σ_i (w_i/W)(x_i/x̄)·ln(x_i/x̄) population-weighted
Gini and Theil-T over the accessibility distribution                                     (30)
```

Figure 20: The distance-decay function behind two-stage floating catchment accessibility, and the population share



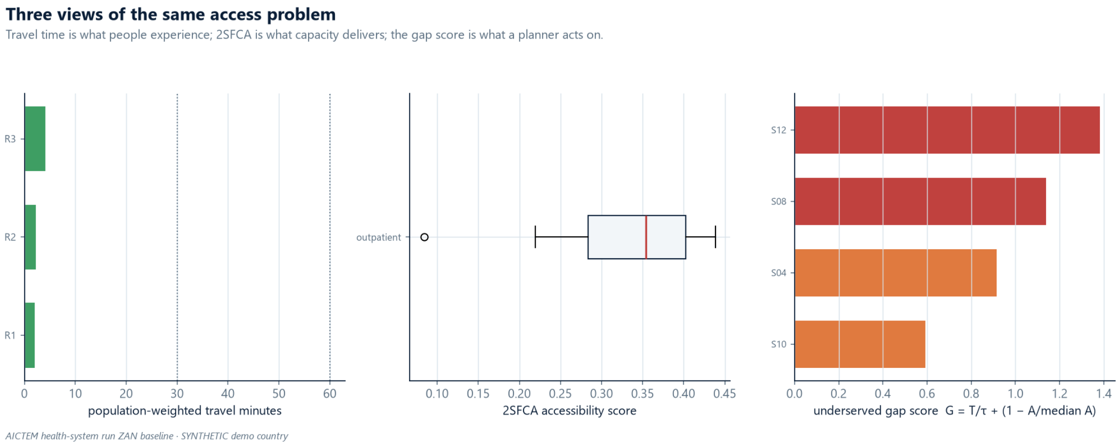
Notes: within each travel-time threshold. Source: EDIS health-system run ZAN baseline · SYNTHETIC demo country.

WHY NEAREST-FACILITY DISTANCE IS THE WRONG DEFAULT

A clinic five kilometres away serving forty thousand people is not more accessible than one eight kilometres away serving four thousand. Nearest-facility distance says it is. Two-stage floating catchment says it is not, because the first step divides capacity by the population that can reach it. Where capacity data exists, 2SFCA is the measure to publish; where it does not, say that distance is all you have.

25.4 What the run produced

Figure 21: Modelled travel time to the nearest facility and the 2SFCA accessibility score, for the demo geography the



Notes: health-system engine runs on. Source: EDIS health-system run ZAN baseline · SYNTHETIC demo country.

Table 148: Threshold coverage, Zandia (ZAN) — the health-system engine's SYNTHETIC demo country

Threshold	Population share within it
30 minutes	100.0 %
60 minutes	100.0 %
90 minutes	100.0 %
120 minutes	100.0 %

Notes: Source: Zandia (ZAN), committed run.

Coverage at every threshold is complete in the demo geography, which is a property of the demo settlement layout rather than a finding. The measure that discriminates there is the two-stage floating catchment score and the underserved gap, both of which vary substantially across origins.

26. Optimisation

Four mathematical programmes, all solved with HiGHS, all taking their parameters from configuration rather than from the survey. This is the chapter where the model stops describing and starts recommending — and where the objective function becomes the most important assumption in the estate.

Table 149: The optimisation block, `Optimization/*.jl` — 10 modules

ID	What it computes	Function
H-OPT-01	Facility planning MILP	`plan_facilities`
H-OPT-02	Workforce allocation MIP	`optimize_workforce_allocation`
H-OPT-03	Referral network LP	`optimize_referral_network`
H-OPT-04	Supply distribution LP	`optimize_supply_distribution`

26.1 Facility planning

EQ. H-OPT-01 FACILITY PLANNING MILP

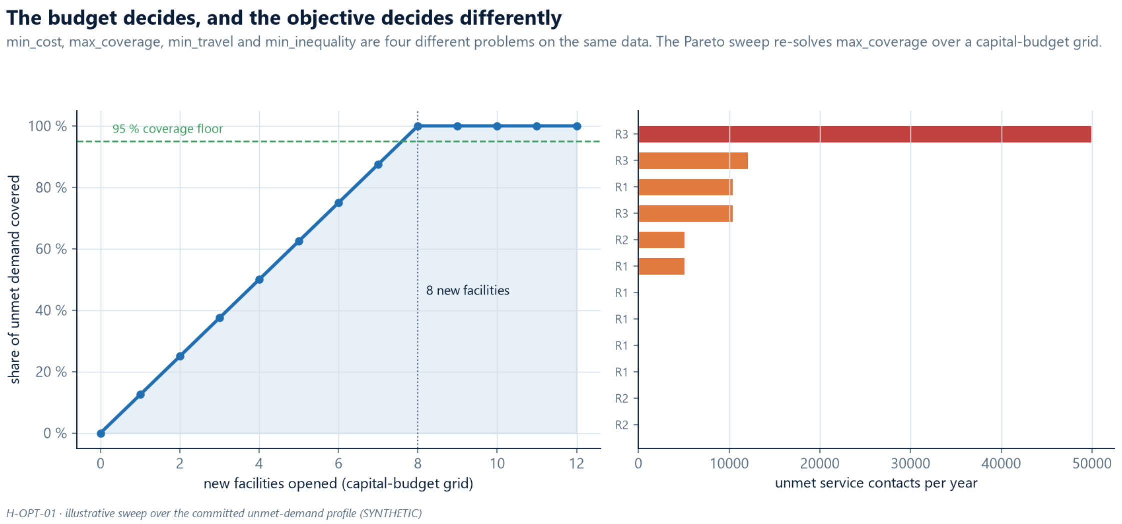
```
min Σ_j capital_j·open_j + Σ_j operating_j·open_j
   + Σ travel_cost·T·x + penalty·Σ_i unmet_i

s.t.  Σ_f x^ex_{if} + Σ_j x^ca_{ij} + unmet_i = DEMAND_i
     Σ_i x^ex_{if} ≤ CAP_f
     Σ_i x^ca_{ij} ≤ capacity_j · open_j
     x_{i·} = 0 if T > max_travel_min
     Σ_j capital_j·open_j ≤ capital_budget
     Σ_i unmet_i ≤ (1 − min_coverage)·Σ DEMAND
     open_j ∈ {0,1}, x ≥ 0, unmet ≥ 0
plan_facilities in Optimization/FacilityPlanning.jl                        (31)
```

Table 150: Five objectives on the same data

Objective	What it minimises or maximises	Who asks for it
min_cost	capital + operating + travel + unmet penalty	a finance ministry
max_coverage	share of demand served	a programme manager
min_unmet	total unserved demand	a service planner
min_travel	population-weighted travel	a community
min_inequality	the worst region's unmet share, min t s.t. $\Sigma_{i\in r}$ unmet_i $\leq$ t·DEMAND_r $\forall$r	an equity mandate

Notes: They do not agree.

Figure 22: The facility-planning trade-off



Notes: coverage achieved against the capital budget, and the objectives that change the answer. Source: Equation H-OPT-01 · illustrative Pareto sweep on the committed unmet-demand profile.

THE OBJECTIVE IS A NORMATIVE CHOICE, NOT A TECHNICAL ONE

min_cost and min_inequality will site facilities in different places, and neither is wrong. The Pareto frontier — re-solving max_coverage over a capital-budget grid — makes the trade-off visible rather than resolving it. A recommendation reported without its objective is a political choice presented as a technical result, and it is on this course's automatic-fail list.

26.2 Workforce allocation

EQ. H-OPT-02 WORKFORCE ALLOCATION MIP

```
min Σ_{r,c} shortfall_{rc} + λ · Σ_c maxsf_c

s.t.  have_{rc} + hire_{rc} + shortfall_{rc} ≥ need_{rc}
      Σ salary_c · hire_{rc} ≤ wage_budget
      shortfall_{rc} ≤ maxsf_c
      hire ∈ ℤ+
the λ term penalises the worst region, which is what stops the solver concentrating hires where they
are cheapest                                                                                  (32)
```

26.3 Referral network

EQ. H-OPT-03 REFERRAL NETWORK LP

```
min Σ_{o,d} T_{od} · flow_{od} + 1000 · Σ_o unref_o

s.t.  Σ_d flow_{od} + unref_o = refdem_o
      Σ_o flow_{od} ≤ 0.30 · CAP_d
the 0.30 cap reserves seventy per cent of a receiving facility's capacity for its own catchment    (33)
```

26.4 Supply distribution

EQ. H-OPT-04 SUPPLY DISTRIBUTION LP

```
min Σ transport_cost · ship + 100 · Σ shortage

s.t.  Σ_f ship_{mwf} ≤ stock_{mw}
      Σ_w ship_{mwf} + short_{mf} ≥ demand_{mf}                                              (34)
```

26.5 What a solver report must carry

- Status — optimal, feasible, infeasible or time-limited. A result from a non-optimal solve is not a recommendation.
- Objective value and the optimality gap — a mixed-integer solve that stopped at a two per cent gap has not proved optimality, and the gap belongs in the report.
- Binding constraints — which constraint stopped the solver is the actionable finding. If the budget binds, more money helps; if the travel constraint binds, money does not.
- Coverage and equity impact — both, because an objective that improves one usually worsens the other.
- Sensitivity — where a ± 25 per cent change in a parameter flips the recommended portfolio.

AN INFEASIBLE EQUITY FLOOR IS A FINDING, NOT AN ERROR

An equity floor φ can be unaffordable at a given budget. The model reports the conflict and the budget that would resolve it rather than returning zeros, because the alternative is a policy choice and not a modelling detail. A planner told 'no solution' learns nothing; a planner told 'the floor you specified requires 1.4 times this budget' has a decision to make.

27. Health financing, costing and value

Everything upstream produces physical quantities: contacts, full-time equivalents, medicine units, beds. This chapter turns them into money, and the exchange rate between the two is a set of external parameters that no household survey contains.

Table 151: The financing block, `Models/HealthFinancing.jl`

ID	What it computes	Function
H-F-01	Service cost	
H-F-02	Financing envelope	`financing_envelope`
H-F-03	Required expenditure & gap	`financing_summary`
H-F-04	Bottom-up input costing	`input_costing`
H-F-05	Cost-effectiveness	`cost_effectiveness`
H-F-06	Fiscal space	`fiscal_space`

EQ. H-F-01 TO H-F-03 COST, ENVELOPE, REQUIREMENT AND GAP

```
COST[r,k] = q[r,k] · unit_cost_k

FIN = government + donor + insurance + OOP
      extrapolated ·(1+budget_growth)^k beyond the budget table

imported = commodity_cost · mean(import_share)
REQ = recurrent + commodity_cost + workforce_cost
                + imported · import_tariff
GAP = max(0, REQ − FIN)
per_capita = REQ / POP                                          (35)
```

EQ. H-F-04 BOTTOM-UP INPUT COSTING

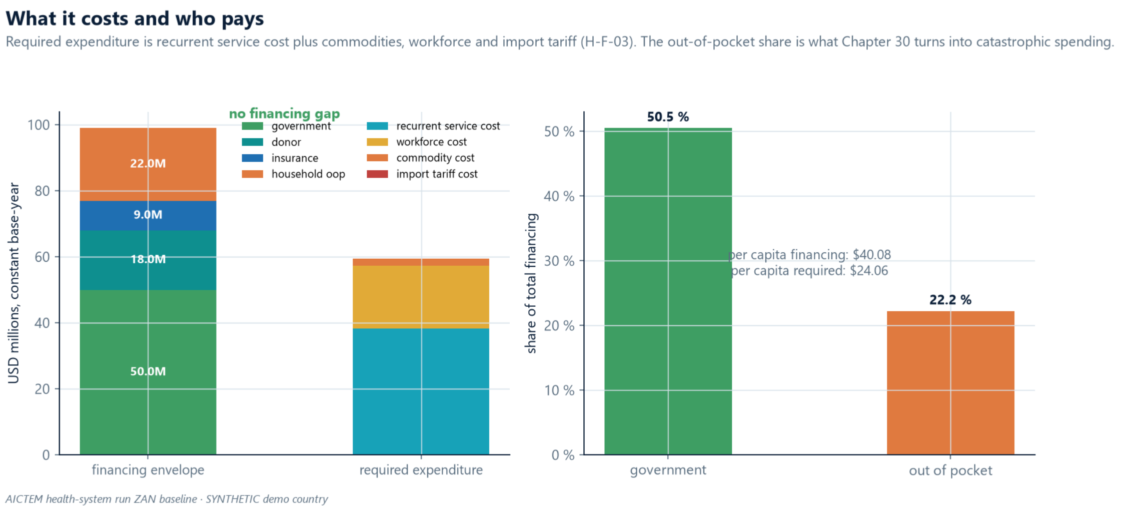
```
Workforce = Σ_c FTE_c · salary_c · salary_mult
Medicines = Σ_m units_m · unit_cost_m · medicine_mult
Infrastructure = beds · bed_annual_cost
Consumables = Σ_k service_cost_k · consumable_mult
Transport = ambulances · ambulance_annual_cost
Utilities = n_facilities · utilities_per_facility
Equipment&labs = equipment_share ·
                 (Workforce + Medicines + Consumables)
Maintenance = maintenance_rate ·
                 (Infrastructure + Equipment)
GRAND = Σ categories
every multiplier is an adjustable configuration parameter       (36)
```

EQ. H-F-05, H-F-06 COST-EFFECTIVENESS AND FISCAL SPACE

```
ICER = △Cost / △DALYs_averted

highly cost-effective if ICER < GDP per capita
cost-effective if ICER < 3 × GDP per capita

Abuja gap = max(0, 0.15·revenue − gov_health)
domestic revenue gap = max(0, REQ − CHE)
the WHO-CHOICE thresholds, and the Abuja Declaration target of fifteen per cent of government revenue
(37)
```

27.1 What the run produced

Figure 23: The financing envelope against required expenditure, and the bottom-up cost build



Notes: Source: EDIS health-system run ZAN baseline · SYNTHETIC demo country.

Table 152: Financing summary, Zandia (ZAN) — the health-system engine's SYNTHETIC demo country

Component	**Value**
Government	$50.0M
Donor	$18.0M
Insurance	$9.0M
Household out-of-pocket	$22.0M
Total financing	$99.0M
Recurrent service cost	$38.3M
Workforce cost	$19.0M
Commodity cost	$2.1M
Imported commodities	$1.7M
Import tariff	$84k
Required expenditure	$59.4M
Financing gap	$0.00
Per capita financing	$40.08
Per capita required	$24.06
Government share	50.5 %
Out-of-pocket share	22.2 %

Notes: Source: Zandia (ZAN), committed run.

A COSTING RESULT IS A STATEMENT ABOUT ITS PARAMETERS

Unit costs, salaries, bed costs and the import share are external planning parameters. A financing gap that closes when the salary multiplier moves five per cent is a result about the salary multiplier. The sensitivity table belongs beside the headline, not in an annex.

28. Health outcomes — deaths and DALYs

The last physical step: turning cases and deaths into a single burden measure that can be compared across diseases and traded off against cost.

Table 153: The outcomes block

ID	What it computes	Function
H-O-01	Deaths with treatment	
H-O-02	Years of life lost	
H-O-03	Years lived with disability	
H-O-04	DALYs & averted	

EQ. H-O-01 TO H-O-04 DEATHS, YLL, YLD AND DALYs

```
DEATHS[r,d,t] = DEATHS0 · (1 − efficacy_d · treatment_coverage(t))
YLL = DEATHS · D(LE_deathage, ρ)
YLD = CASES · DW_d · D(duration_d, ρ)
DALY = YLL + YLD
deaths_averted = DEATHS0 − DEATHS
D(L,ρ) is the discounted present value of L annual life-years, from H-O-02        (38)
```

Table 154: Reference defaults by disease category, from `Models/Reference.jl`

Disease category	Disability weight	Duration (years)	Age of death
Communicable	0.19	0.05	5–14
Non-communicable	0.20	8.0	50–64
Maternal	0.32	0.10	15–49
Neonatal	0.38	0.08	0–4
Nutrition	0.12	0.30	0–4
Injury	0.18	0.20	15–49

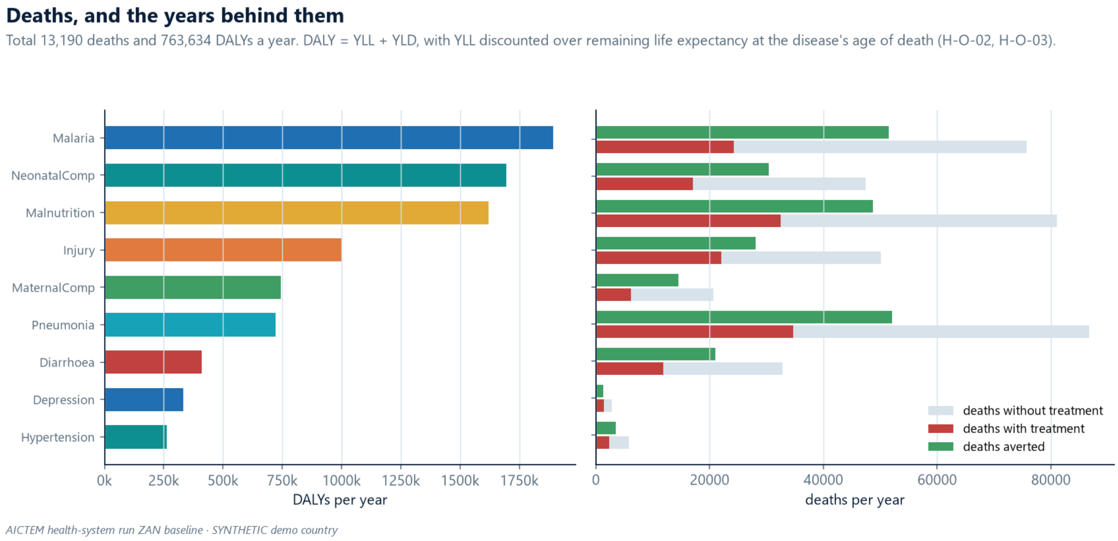
Notes: Overridable per disease.

Table 155: Reference remaining life expectancy, used by YLL

Age group	Remaining life expectancy (years)
0–4	86.0
5–14	78.5
15–49	56.0
50–64	29.0
65+	13.0

28.1 What the run produced

Figure 24: Health outcomes



Notes: deaths averted by treatment coverage, and the disability-adjusted life years each disease carries. Source: EDIS health-system run ZAN baseline · SYNTHETIC demo country.

THREE PARAMETERS CARRY THE WHOLE RESULT

The disability weight, the duration and the age of death are reference-table defaults unless a disease overrides them. Change the assumed age of death for a communicable disease from 5–14 to 0–4 and its years of life lost rise by roughly ten per cent before anything else changes. A DALY comparison across diseases is a comparison of these parameters as much as of the diseases, and Chapter 36 requires them to be stated.

29. Climate–health risk

Two exposure-response functions, both bounded, both turning over. This chapter is short because the mechanics are simple and the misuse is common.

Table 156: The climate block, `GIS/ClimateRisk.jl`

ID	What it computes	Function
H-CL-01	Heat–mortality exposure-response	`heat_mortality_rr`
H-CL-02	Malaria climate envelope	`malaria_suitability`
H-CL-03	Attributable climate burden	`climate_health_burden`
H-CL-04	Heat-attributable deaths	`heat_attributable_deaths`
H-CL-05	Facility exposure & resilience	`facility_climate_exposure`

EQ. H-CL-01 HEAT–MORTALITY J-CURVE

$$RR(T) = 1 + 0.03\cdot(T - MMT) + 0.002\cdot(T - MMT)^2 \quad T \geq MMT$$
$$RR(T) = 1 + 0.015\cdot(MMT - T) \quad T < MMT$$

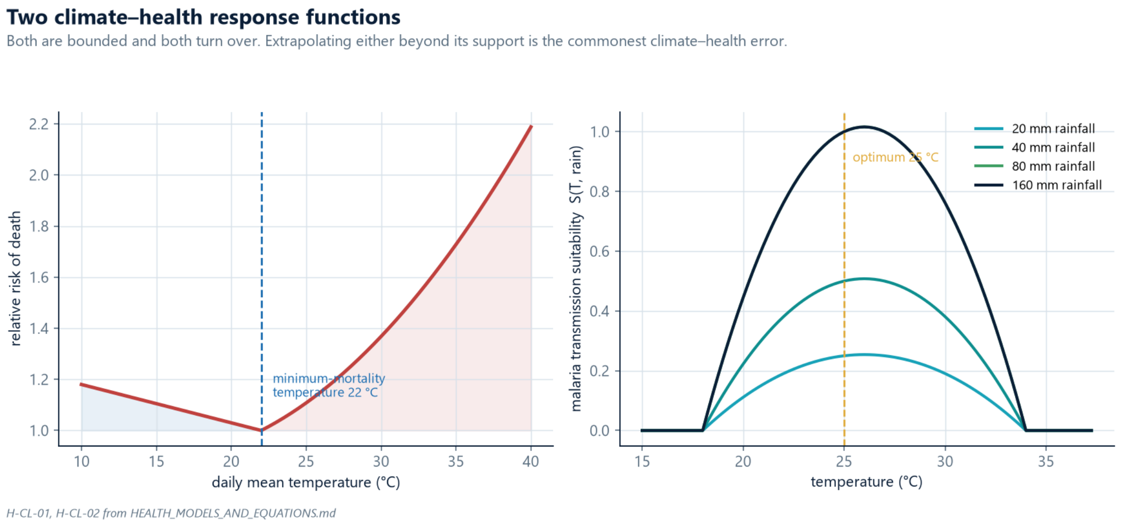
$$\text{MMT} = 22\ ^\circ\text{C, the minimum-mortality temperature} \tag{39}$$

EQ. H-CL-02 MALARIA CLIMATE ENVELOPE

$$\begin{aligned} S(T,\ \text{rain}) = {} & [\ (T-18)(34-T)\ /\ ((25-18)(34-25))\ ]_{+} \\ & \cdot\ \text{clamp}(\text{rain}/80,\ 0,\ 1) \end{aligned}$$

$$\text{support } T \in (18,\ 34)\ ^\circ\text{C, optimum } 25\ ^\circ\text{C} \tag{40}$$

Figure 25: The heat–mortality J-curve (H-CL-01) and the malaria climate envelope (H-CL-02), as the model implements them



Notes: Source: Equations H-CL-01 and H-CL-02.

EQ. H-CL-03 TO H-CL-05 ATTRIBUTABLE BURDEN AND FACILITY EXPOSURE

$$\begin{aligned} &\text{extra\_cases} = \text{base\_cases} \cdot \text{elasticity\_d} \cdot \Delta T \cdot S \\ &\text{extra\_deaths} = \text{extra\_cases} \cdot \text{CFR} \end{aligned}$$

$$\begin{aligned} \text{heat deaths} = {} & \text{baseline\_deaths} \cdot (RR(T)/RR(T_0) - 1), \\ & \text{baseline\_deaths} = 0.008 \cdot \text{POP} \end{aligned}$$

$$\begin{aligned} &\text{resilience} = (\text{electricity} + \text{water} + \text{cold\_chain})/3 \\ &\text{exposure} = \text{flood} \cdot (1 - 0.5 \cdot \text{resilience}) \\ &\text{at risk if exposure} > 0.35 \end{aligned} \tag{41}$$

29.1 What the run produced

Table 157: Attributable climate burden, Zandia (ZAN) — the health-system engine's SYNTHETIC demo country (extract)

Area	Disease	Scenario	ΔT	Extra cases	Extra deaths
R1	Malaria	baseline	0.00	0.0	0.00
R1	Diarrhoea	baseline	0.00	0.0	0.00
R1	Pneumonia	baseline	0.00	0.0	0.00
R1	Tuberculosis	baseline	0.00	0.0	0.00
R1	NeonatalComp	baseline	0.00	0.0	0.00
R1	Depression	baseline	0.00	0.0	0.00
R1	Malnutrition	baseline	0.00	0.0	0.00
R1	Injury	baseline	0.00	0.0	0.00
R2	Malaria	baseline	0.00	0.0	0.00
R2	Diarrhoea	baseline	0.00	0.0	0.00
R2	Pneumonia	baseline	0.00	0.0	0.00
R2	Tuberculosis	baseline	0.00	0.0	0.00
R2	NeonatalComp	baseline	0.00	0.0	0.00
R2	Depression	baseline	0.00	0.0	0.00

Notes: Source: Zandia (ZAN), committed run.

The facility exposure assessment covers 9 facilities and flags 1 as at risk — exposure above 0.35 after resilience is netted off. Resilience here is the mean of three binary indicators: electricity, water and cold chain.

BOTH FUNCTIONS TURN OVER, AND BOTH HAVE A SUPPORT

The heat curve is a J: mortality rises on both sides of the minimum-mortality temperature, and a linear warming term will get the cold side backwards. The malaria envelope is zero outside 18–34 ℃ and peaks at 25 ℃, so warming can *reduce* suitability where it is already near the optimum. Extrapolating either beyond its support is the commonest climate-health error, and both are elasticity-driven with elasticities that are configuration parameters rather than estimates from these data.

Part V — Distribution and integration

Who pays and what it costs them; and what leaves the health estate for the rest of the platform.

30. Poverty, welfare and financial protection

Chapter 27 produced a financing envelope with an out-of-pocket share in it. This chapter is about the households behind that share, because a national average of out-of-pocket spending hides the households it ruins.

Table 158: The poverty block, `Integration/Poverty.jl`

ID	What it computes	Function
H-P-01	OOP after policy	`apply_health_policy`
H-P-02	Consumption after payment	
H-P-03	Catastrophic — budget share	
H-P-04	Catastrophic — WHO capacity-to-pay	
H-P-05	Impoverishment	
H-P-06	Poverty headcount / gap	
H-P-07	Concentration index of OOP	
H-P-08	Gini	

EQ. H-P-01, H-P-02 OUT-OF-POCKET AFTER POLICY

```
OOP_h = base_oop_h · oop_shock · (1 − user_fee_removal)
                              · (1 − medicine_subsidy)
  insured → × 0.50
  newly insured → × 0.30 (share insurance_expansion)
post_h = cons_h − OOP_h / size_h
pw_h = weight_h · size_h person weight                                    (42)
```

EQ. H-P-03 TO H-P-05 CATASTROPHIC SPENDING AND IMPOVERISHMENT

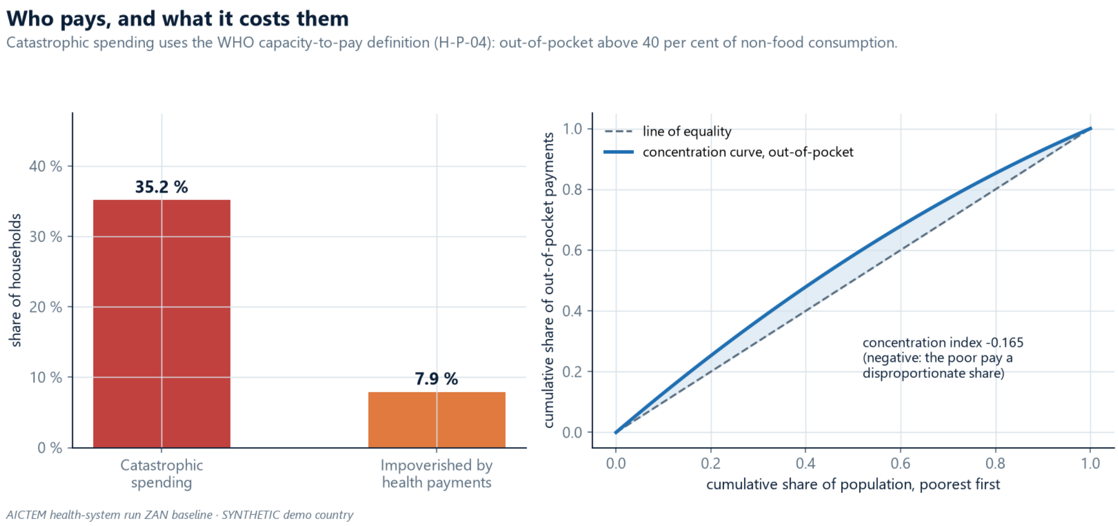
```
budget share:  1[ OOP_h / (cons_h·size_h) > 0.10 ]
capacity to pay:  nonfood_h = cons_h·size_h·(1 − foodshare_q)
                   foodshare_q = clamp(0.72 − 0.06(q−1),
                                       0.35, 0.78)
                   catastrophic if OOP_h / nonfood_h > 0.40
impoverishment:  1[ post_h < line ∧ pre_h ≥ line ]
two definitions, and they do not agree - the WHO capacity-to-pay measure is the one to publish      (43)
```

EQ. H-P-06 TO H-P-08 POVERTY, PROGRESSIVITY AND REDISTRIBUTION

```
HC = Σ pw·1[y < line] / W headcount
Gap = Σ pw·max(0, (line − y)/line) / W poverty gap
CI = (2/(W·ȳ))·Σ w·y·rank − 1 concentration index
Kakwani = CI_oop − Gini_pre > 0 progressive
Redistributive effect = Gini_pre − Gini_post
Financial protection index = 1 − catastrophic_rate                        (44)
```

30.1 What the run produced

Figure 26: Financial protection



Notes: out-of-pocket payments pushing households past the catastrophic threshold and below the poverty line. Source: EDIS health-system run ZAN baseline · SYNTHETIC demo country.

Table 159: Financial protection, Zandia (ZAN) — the health-system engine's SYNTHETIC demo country

Indicator	Value	Reading
Catastrophic spending rate	35.2 %	households paying more than 40 % of non-food consumption
Impoverishing rate	7.9 %	households pushed below the line by health payments
Concentration index of out-of-pocket	-0.1648	negative: the poor bear a disproportionate share

Notes: Source: Zandia (ZAN), committed run.

30.2 Calibration to a population

Converting a weighted survey proportion into a population count is a raking operation. The system uses iterative proportional fitting against external margins and trims the resulting weights to between 0.25 and 4 times the original.

WHY THE TRIM EXISTS

Unbounded raking can give one household a weight ten times its neighbours'. Every subsequent estimate then rests on that household, and its confidence interval will not say so. Where calibration fails to converge inside the trim, results are labelled survey-population-only — which means they must not be quoted as national counts.

30.3 The zero-shock test

THE CHECK THAT CATCHES ALMOST EVERYTHING

Run the microsimulation with every lever at its baseline value. The result must reproduce the baseline weighted indicators within tolerance. It catches weight handling, re-prediction bugs, aggregation errors and covariate-alignment mistakes in a single check. Run it before you run anything interesting.

30.4 Scenarios, and why they are not additive

Table 160: Scenario comparison with the explicit interaction row, Uganda 2016 DHS (UG2016DHS)

Scenario	Change	95 % CI	n	Status
baseline	+0.0 pp	+0.0 pp to +0.0 pp	4,423	ok
nutrition_package	-2.8 pp	-4.7 pp to -1.0 pp	4,423	ok
combined_policy	+0.0 pp	+0.0 pp to +0.0 pp	4,423	ok
INTERACTION (joint - sum of parts)	+2.8 pp	—	0	joint=0.0 vs sum=-0.0282

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

READ THE INTERACTION ROW

The combined scenario returns no change while its component returns a reduction, and the final row states the joint effect against the sum of the parts. A lever the data cannot identify is dropped, not guessed, and the status column says which. Reporting the sum of the parts as the combined effect is the error that row exists to prevent.

Uncertainty on a scenario is bootstrapped on the **change**, clustered on the primary sampling unit — not on the two levels separately. Baseline and scenario come from the same records with the same weights, so their errors are almost perfectly correlated; differencing two independent intervals produces an interval on the change that is far too wide.

31. Macro, CGE and education integration

The health estate does not close the loop to the economy by itself, and this chapter is about being precise on what it does instead.

Table 161: The integration block, `Integration/*.jl`

ID	What it computes	Function
H-M-01	Exchange objects	
H-M-02	Iterative convergence	`iterate_health_macro`
H-M-03	CDCGE adapter	`read_cdcge_results`
H-M-04	Education linkage	`education_demand`

31.1 The exchange objects

Table 162: Every field is a physical or fiscal quantity the health estate can defend

Object	What it carries
`HealthToMacroResults`	government health consumption and investment, public and private employment, the wage bill, medicine and equipment imports, domestic pharmaceutical demand, construction, productivity, labour participation, mortality, morbidity work-days lost, household health spending, insurance contributions, fiscal cost and foreign financing
`MacroToHealthInputs`	GDP, population, inflation, exchange rate, revenue, expenditure ceiling, wage index, import price index, interest, poverty, employment and income
`HealthToCGEResults` / `CGEToHealthInputs`	the CGE-facing pair, exchanged as files

EQ. H-M-02, H-M-04 CONVERGENCE LOOP AND EDUCATION DEMAND

```
iterate_health_macro:  health → macro → health
                       until |Δ fiscal_cost| < tol
                       or max_iter reached

intake_c = (replacement_c + gap_c/horizon)
           / (1 − training_attrition)
the education link converts a workforce gap into an annual training intake        (45)
```

31.2 The CDCGE adapter

`read_cdcge_results` reads a CDCGE tidy results export — scenario, period, series, value — and `cdcge_to_health` maps GDP, household income and the temperature anomaly into the health configuration's climate and income signals. The CGE is not duplicated and is not re-solved.

HL-09 — ONE DIRECTION, AND SAY SO

There is no two-way solve and no iteration to convergence against a live macro model. `iterate_health_macro` exists and works, but it needs a macro step function to converge against and this estate does not have one wired. A result presented as a health-macro equilibrium is a claim this estate cannot support.

31.3 What never crosses

NO CURRENCY VALUE IS MANUFACTURED FROM A HOUSEHOLD SURVEY

The macro export refuses, in writing, to attach monetary productivity losses: a household survey contains no wages, no output and no hours. The receiving module applies its own elasticities to the physical indicators the health estate supplies. The same rule blocks converting an asset-index wealth quintile into a poverty line — that needs an explicit external bridge from a survey carrying both.

32. The cross-sector handover

The last chapter of the modelling chain. What leaves the estate, what is refused, and the four sentences that travel with every number.

32.1 The manifest

Table 163: `outputs/cross_sector/_manifest.json`

Field	Value
Survey	UG2016DHS
Configuration digest	`6f173f8de3c0eddf`
Disclosure threshold	25
Links attempted	7
Exported	5
Skipped	2

32.2 What was exported, and what each export refused

poverty_microsim →EDIS_Poverty_Microsimulation

19,588 rows exported.

> **REFUSED FIELDS**
>
> Any monetary income or consumption. The DHS wealth index is an ordinal asset index; converting it to money requires an explicit external bridge (a survey with both), which must be supplied by the poverty module.

education →EDIS_Education

15 rows exported.

> **REFUSED FIELDS**
>
> School attendance/attainment of children — DHS household schedules cover attendance only partially and are not a substitute for EMIS/MICS data.

macro_cdcge →EDIS_CDCGE

15 rows exported.

REFUSED FIELDS

Monetary productivity losses. DHS contains no wages, output or hours. The macro module must apply its OWN elasticities to these physical indicators; this system will not manufacture a currency value. • Days lost to illness beyond the 2-week recall of child illness modules.

energy →EDIS_Energy

15 rows exported.

REFUSED FIELDS

Facility electrification status and priority ranking. DHS surveys HOUSEHOLDS, not facilities. Facility-level energy conclusions require an SPA/HHFA facility census; without `imports.facilities.electrified` this export is emitted with the population columns only and a REFUSED flag on the electrification-priority columns. • facility_electrification_priority and cold_chain_failure_risk: no external facility-energy register supplied. The DHS household electrification rate is NOT a proxy for facility electrification.

agriculture_food →EDIS_Agriculture

180 rows exported.

REFUSED FIELDS

Household dietary diversity / food-consumption scores — not collected by standard DHS (use LSMS/FIES).

32.3 What did not cross at all (HL-08)

Table 164: Skipped links, their stated reasons, and the input that would activate each

Link	Target	Reason	What would activate it
transport	EDIS_Transport	no accessibility surface (needs the GE recode and an external facility register)	the survey GPS recode plus an external facility register — Chapter 25 has both for Uganda
climate	EDIS_Climate	no climate-linked risk functions (needs external climate layers)	gridded climate layers; the estate registers CHIRPS and WorldClim but holds them for very few countries (HL-12)

A skipped link is a published result. It tells the receiving module exactly what additional data would activate it, which is more useful than an export full of nulls.

32.4 Bridge matrices must reconcile

A survey wealth quintile is not a CGE representative household, and a survey education category is not a labour factor. The mapping is a declared matrix, and the sum of the mapped shares must return the weighted total. If it does not, the bridge is wrong and the receiving model absorbs the error silently.

32.5 The handover statement

Four sentences, short because they will be read by someone who did not do the analysis.

THE HANDOVER STATEMENT

```
WHAT THIS IS the indicator or quantity, the model that
                  produced it, the population or geography, and
                  the denominator
WHAT IT IS ON real survey evidence with a design-based
                  interval, OR a parameterised system-model
                  result with a sensitivity range, OR an
                  optimisation result under a stated objective
WHAT IT IS NOT not an effect unless the causal module produced
                  one; not a monetary value derived from a
                  household survey; not evidence about a real
                  country if it is labelled SYNTHETIC
WHAT WOULD the assumed parameters, and the range over
CHANGE IT which the conclusion holds
```

Chapter 36 gives the templates for each of the three kinds of claim.

Part VI — Validation, examples and practice

What the system checks, four calculations done by hand, three case studies, how to write the result down, and where it goes wrong.

33. Validation and diagnostics

33.1 The population-health check suite

242 checks across 27 cohorts run before anything is estimated; 241 pass and 1 does not.

NO_SINGLETON_STRATA — COHORT:ZERO_DOSE

1 singleton strata (treated as certainty units; SEs there are conservative) Chapter 4.2 explains why a singleton stratum is treated as a certainty unit rather than dropped: dropping it would silently change the estimation population.

33.2 Four levels of validation, and which this estate has

Table 165: The four levels

Level	What it compares	Present?
Internal identity	an output against an accounting identity it must satisfy	yes — mirror invariance of the Erreygers index, the closed-population identity in SIR, inventory balance, and zero-shock reproduction
Recovery on synthetic data	an estimate against the known generating parameter	yes — including the synthetic average treatment effect of 0.12, which the causal module's interval covers
Cross-implementation	two independent implementations of one definition	yes — 5 indicators, agreement to machine precision
External benchmark	an estimate against a published national figure	**no** — no external ground truth was supplied (HL-11)

Table 166: Julia against R on Uganda 2016 DHS (UG2016DHS)

Indicator	Julia	R	|difference|
stunting	0.2816031542	0.2816031542	5.0e-16
facility delivery	0.7336211907	0.7336211907	1.1e-16
modern contraception	0.3476230896	0.3476230896	2.8e-16
zero dose	0.0550892293	0.0550892293	6.9e-18
anaemia child	0.5376278186	0.5376278186	4.4e-16

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

DO NOT OVERSTATE THE CROSS-CHECK

Two engines agreeing to sixteen decimal places is a strong result about implementation and says nothing about definition. If both read the same indicator dictionary and that dictionary defines an indicator differently from the national report, they agree precisely on the wrong number.

33.3 What the system-model side is validated against

Table 167: From `IMPLEMENTATION_STATUS.md` and `HEALTH_SYSTEM_VALIDATION_REPORT.md`

Component	Evidence	Status
Test suite	243 of 243 checks on synthetic fixtures generated from a known process	passing
End-to-end run	49 of 49 stages on a real survey	passing
Epidemiology	mass-balance identities asserted; SIR and SEIR uncalibrated to the demo diseases	implemented, not calibrated (HL-03)
Optimisation	solver status, objective and gap reported on every solve	HiGHS; Ipopt and PATHSolver available and unused
Accessibility	node graph with a great-circle fallback	partial routing (HL-04)
Macro and CGE	exchange objects and the loop exist; no live macro step	framework (HL-09)

33.4 The refuse-to-ship gate

Table 168: `make security-audit`

Check	Result on the committed run
Staging area empty	PASSED
No identifier or coordinate column in any output	PASSED across 613 CSV outputs
Every disclosed cell meets the denominator threshold	PASSED at n $\geq$ 25
Every estimate table carries uncertainty	PASSED
Every output has a provenance sidecar	367 sidecars written
Registry clean	PASSED

34. Worked numerical examples

Five calculations, done by hand against numbers the estate produced. Each is reproduced by a script in `09_Code/Julia/`.

34.1 A design-based interval, from first principles

WORKED 1 — STUNTING, Uganda 2016 DHS (UG2016DHS)

$$\begin{aligned}
&\texttt{weighted prevalence } \hat{p} = 0.281603\\
&\texttt{design-based SE SE_d} = 0.008705\\
&\texttt{unweighted n} = 4{,}423\\
&\texttt{naive SRS SE} = \sqrt{(\hat{p}(1-\hat{p})/n)} = 0.006763\\
&\texttt{design effect} = (\texttt{SE_d/SE_srs})^2 = 1.6569\\
&\qquad\qquad\qquad\texttt{reported} = 1.6569\\
&95\ \%\ \texttt{CI (design)} = 0.2645 \texttt{ to } 0.2987\\
&95\ \%\ \texttt{CI (naive)} = 0.2683 \texttt{ to } 0.2949
\end{aligned} \tag{46}$$

The design-based interval is 1.29 times wider. A two-point gap between regions can be significant under the naive interval and not under the design-based one, and only one of those describes the survey that was run.

34.2 Odds ratio, risk ratio and marginal effect

WORKED 2 — THREE SCALES FOR ONE COEFFICIENT

$$\begin{aligned}
&\beta\ \texttt{(log-odds)} = 1.30024\\
&\texttt{OR} = \exp(\beta) = 3.6702\\
&\texttt{baseline } p_0 = 0.2816\\
&o_0 = p_0/(1-p_0) = 0.3920\\
&o_1 = o_0 \times \texttt{OR} = 1.4387\\
&p_1 = o_1/(1+o_1) = 0.5899\\
&\texttt{risk ratio } p_1/p_0 = 2.095\\
&\texttt{AME} \approx p_0(1-p_0)\cdot\beta = 0.26304\ (+26.3\ \texttt{pp})
\end{aligned} \tag{47}$$

An odds ratio of 3.67 is a risk ratio of about 2.09 at this prevalence. A minister told the first as 'times more likely' has been told something about 1.8 times too strong.

34.3 Chaining interval hazards into a mortality rate

WORKED 3 — DECOMPOSING UNDER-FIVE MORTALITY, Uganda 2016 DHS (UG2016DHS)

```
q(neonatal) = 0.02727 (27.3 per 1,000)
q(infant) = 0.04622 (46.2 per 1,000)
q(under-five) = 0.06865 (68.7 per 1,000)

post-neonatal = 1 − (1−q_inf)/(1−q_neo)
              = 19.5 per 1,000

child 12-59 mo = 1 − (1−q_u5)/(1−q_inf)
               = 23.5 per 1,000                                        (48)
```

About 40 % of under-five deaths occur in the first twenty-eight days. The components chain as conditional survival probabilities; they do not add.

34.4 From cases to a workforce requirement

WORKED 4 — THE CHAIN FROM EPIDEMIOLOGY TO STAFFING, Zandia (ZAN) — the health-system engine's SYNTHETIC demo country

```
NEED[r,k] = Σ_{d→k} CASES[r,d] · υ_k
DEMAND = NEED · seeking · coverage · PriceFactor
AWT_c = hours_c · 60 · (1 − absent_c)
NEED[c,r] = 1.15 · Σ_k DEMAND[r,k]·σ_k·ψ_{c,k} / AWT_c

total demand on the committed run = 1,041,366 contacts/yr
total WISN requirement = 507.9 FTE

implied contacts per FTE per year = 2,050                              (49)
```

The last line is the sanity check. If contacts per full-time equivalent comes out at a number no clinician could deliver, the error is upstream — in the visits-per-case parameter, the care-seeking rate or the staff-minutes table — and not in the workforce model.

34.5 A Fay–Herriot estimate by hand

WORKED 5 — WHAT SHRINKAGE ACTUALLY DID

```
area = bugisu
direct estimate y_a = 0.36291 (SE 0.04210)
shrinkage γ_a = 0.73616
EBLUP θ̂_a = 0.34096 (SE 0.03612)

θ̂_a = x_a'β̂ + γ_a(y_a − x_a'β̂), so the synthetic part is
  x_a'β̂ = (θ̂_a − γ_a y_a)/(1 − γ_a) = 0.27971

model share = 1 − γ_a = 26.4 %
SE reduction = 14.2 %                                                  (50)
```

Variance traded for bias, in one screen. Whether it is a good trade depends on whether the covariates are right, which the model cannot tell you.

35. Case studies

Three cases, supplied in full in `10_Case_Studies/`. Each is about a failure that is organisational as much as technical.

35.1 The plan that was built on nominal capacity

A district health plan is costed against the facility register: so many health centres, so many beds, so many consultation rooms. The plan projects a surplus. Two years later the same facilities are turning patients away. The case follows the difference between nominal and effective capacity through staffing, readiness and opening hours, and shows where the surplus went.

The lesson. Chapter 22's H-C-02 is not a refinement. A plan built on the register is a plan built on a number the system cannot deliver.

35.2 A map that should not have been published

A research group produces a district malaria risk surface from survey clusters, extracting environmental covariates at the released coordinates. The method is defensible in every step and the output points at settlements that were never surveyed. The case covers what displacement did to the estimates, what the map implied, and why no code path in this estate emits a coordinate.

The lesson. Displacement is a disclosure control, not noise. And ranking areas by posterior mean rewards thin samples.

35.3 The odds ratio that reached the cabinet

A correctly executed survey logit reports an odds ratio of 3.7 for maternal education. By the time it reaches a cabinet memo it has become 'nearly four times more likely', and a programme is costed against it. The case follows the sentence through four documents and shows where the marginal effect should have been attached.

The lesson. An odds ratio is not a risk ratio, and the class of claim travels with the number or somebody downstream supplies one.

36. Policy interpretation

This chapter is about writing the result down, and it is the part most often done badly by people who did the analysis well.

36.1 The interpretation rules

1. An estimate is not publishable without its interval, its denominator and its disclosure status

All three come from the design. A number without them implies a precision the sample does not have.

2. An odds ratio is not a risk ratio

At a prevalence of 28 per cent the two differ substantially, and a policy reader will hear the second. Report the average marginal effect alongside every odds ratio.

3. A hazard ratio is a conditional rate comparison

It compares rates among those still at risk in each interval, not cumulative probabilities of dying.

4. Need is not demand, and demand is not utilisation

Need is epidemiological, demand is behavioural, and utilisation is what capacity allowed. The three differ by construction and the model reports all three.

5. Nominal capacity is not effective capacity

Effective capacity is constrained by staffing, readiness and opening hours. Planning against the register overstates what a system can deliver.

6. Distance is not access

Accessibility measures that ignore capacity rank a crowded near clinic above an empty far one. 2SFCA is the measure that does not.

7. A projection is not a forecast

Interpolation, nowcast and forecast are three different statements and the product column names which one each year is.

8. Feature importance is not a causal effect

A permutation-importance ranking says what the model uses, not what an intervention would change.

9. A cross-sectional association is not a causal claim

It becomes one only through a declared identification strategy that passes its gate — and the gate is allowed to refuse.

10. An optimisation result is a statement about its objective and its parameters

Capacity, unit cost and budget are external planning parameters. Four objectives on the same data give four different plans.

11. A spatial prediction is a model-based estimate with uncertainty

A smoothed map that omits the shrinkage weight and the exceedance probability presents the model as data.

12. A suppressed cell is a published result

The denominator stays visible so the reason is legible; deleting the row hides that the question was asked.

36.2 Three templates, for three kinds of claim

TEMPLATE 1 — A POPULATION-HEALTH ESTIMATE

```
ESTIMATE Stunting (height-for-age z < −2), children under 5
SURVEY Uganda 2016 DHS (UG2016DHS)
COHORT living children 0-59 months with a valid z-score
VALUE 28.2 % (95 % CI 26.5-29.9)
DENOMINATOR 4,423 unweighted; design effect 1.66
DISCLOSURE disclosed (n above the threshold of 25)
CLASS descriptive - a weighted population proportion
NOT not attributable to any cause; not a projection
```

TEMPLATE 2 — A SYSTEM-MODEL RESULT

```
RESULT Total unmet service demand
MODEL Health-system engine, H-S-02 through H-C-03
GEOGRAPHY Zandia (ZAN) - the health-system engine's SYNTHETIC demo country
VALUE 92,987 contacts per year, against total demand of 1,041,366
RESTS ON care-seeking rate, coverage target, price elasticity
            0.18, staffing productivity, readiness and opening
            hours - all configuration parameters
CLASS SYNTHETIC - a demonstration, not evidence about any
            real country
WOULD a ten per cent change in the care-seeking rate moves
CHANGE IT demand roughly proportionally; the sensitivity table
            is in the run output
```

TEMPLATE 3 — AN OPTIMISATION RESULT

```
RECOMMENDATION Open N facilities in the listed districts
MODEL H-OPT-01 facility planning MILP, HiGHS
OBJECTIVE max_coverage subject to a capital budget
PARAMETERS capacity per facility, capital and operating
                cost, maximum travel time, coverage floor -
                all external planning parameters
SOLVER status, objective value, optimality gap,
                binding constraints
```

```
UNDER A min_cost sites differently; min_inequality sites
DIFFERENT differently again.  The frontier is in the
OBJECTIVE Pareto sweep.
NOT not a statement that these districts need
                facilities most - that is the underserved gap
                score, which is a different output
```

36.3 Writing for a minister

Table 169: Rewriting five sentences

Instead of	Write
"Stunting is 28.2 %"	"About 28 in every 100 children under five are stunted (95 % CI 26 to 30), measured in 2016 on 4,423 children"
"The model shows we need 37 more staff"	"Under the modelled demand and the current staff-minute assumptions, the workforce requirement exceeds availability by about 37 full-time equivalents. That is a requirement, not a vacancy count"
"The optimum is to build in these five districts"	"Maximising coverage within this capital budget puts facilities in these five districts. Minimising the worst region's unmet share puts them in three different ones; both are on the frontier"
"Health spending is catastrophic for 35 % of households"	"On the WHO capacity-to-pay definition, about 35 per cent of households in the demo geography spend more than 40 per cent of non-food consumption on health. This is a synthetic demonstration, not a measurement of any country"
"District X is worst"	"District X has the highest estimate, but part of that number comes from the model rather than from that district's sample; the exceedance probabilities are the ranking to use"

36.4 The automatic fails

1. Quoting an estimate without its interval, its denominator and its disclosure status.
2. Estimating child mortality from the children's recode rather than from the birth history.
3. Describing an adjusted association as an effect, or an odds ratio as a risk ratio.
4. Mixing a real survey estimate and a synthetic health-system figure in the same statement without labelling both.
5. Reporting an optimisation result without its objective and its external planning parameters.
6. Publishing a cluster coordinate, an identifier, or a cell whose unweighted denominator is below the disclosure threshold.
7. Reporting a projection beyond the evidence window without the label the system attaches to it.

37. Laboratory walkthroughs

Eight laboratories. Full instructions are in `04_Laboratory_Manual.docx`; instructor solutions are in `05_Instructor_Guide.docx`. This chapter is the map.

Table 170: The eight laboratories

Lab	Title	Hours	Covers	Chapters
01	The model estate and the catalogue	2.5	What is in the estate, what ran on each survey, and why the rest did not	1, 3, 5–18
02	Design-based estimation and the cross-check	3.0	An indicator with its interval, design effect and disclosure status, reproduced in a second implementation	4, 33
03	Child survival and the maternal continuum	3.0	Families A and B end to end: rates, hazards, the cascade and the postnatal diagnosis	5, 6, 34
04	Nutrition, morbidity and immunisation	3.0	Families D, F and G: the wealth gradient, the rare-event case and the decode trap	8, 10, 11
05	Inequality, small area and a map that does not leak	3.5	Families L and M: five measures, a decomposition, shrinkage and exceedance	16, 17, 34
06	Demography, epidemiology, demand and capacity	3.5	The engine from the age structure through to unmet demand and the waiting probability	19–22
07	Accessibility and facility optimisation	3.5	Travel time, 2SFCA, the underserved gap, and a facility plan under four objectives	25, 26
08	Financing, DALYs, climate, poverty and the handover	3.0	Cost, gap, cost-effectiveness, burden, climate response and the transfer files	27–32

THE RULE EVERY LABORATORY ENDS WITH

Three sentences: what kind of claim this is, what its uncertainty is, and what would change it. For a survey estimate that is the denominator, the interval and the disclosure status. For a system-model result it is the parameters and the sensitivity range. For an optimisation result it is the objective. They carry the honesty-about-limits mark, which is 20 per cent.

38. Common errors and troubleshooting

Ordered by how much time each one costs before it is found.

38.1 Errors of definition

Table 171: Errors of definition

Symptom	Cause	Fix
Mean height-for-age in the thousands	Anthropometric flag codes 9996–9999 treated as numbers	Apply the decode rule in `variables.yml`
A mortality rate far below the published one	Estimated from the children's recode rather than the birth history	Use the birth history; the other conditions on survival
A biomarker estimate that disagrees with the report	Household weight needed; the women's weight used	The weight follows the recode, not the question
A trend that jumps at one round	A comparability break	`surveys.yml` records them; the system refuses the trend
Need, demand and utilisation quoted interchangeably	Three different quantities	Chapter 21. Say which one the number is

38.2 Errors of design and estimation

Table 172: Errors of design and estimation

Symptom	Cause	Fix
Confidence intervals suspiciously narrow	Simple-random-sample variance on a clustered sample	Use the design; check the reported design effect
Everything is statistically significant	Naive chi-squared under clustering	Rao–Scott correction; report both statistics
A domain estimate whose standard error is wrong	The data were subset before estimation	Keep all records and zero the outside contributions
A cross-validated AUROC that looks too good	Random folds instead of cluster folds	Fold by primary sampling unit
A negative proportional change in variance read as a bug	It is a result	Chapter 17. The covariates did not explain cluster variation

38.3 Errors in the system model

Table 173: Errors in the system model

Symptom	Cause	Fix
A surplus of capacity that does not exist in practice	Planned against nominal rather than effective capacity	H-C-02. Staffing, readiness and hours constrain it
Contacts per full-time equivalent that no clinician could deliver	An upstream parameter — visits per case, care-seeking, or staff-minutes	Chapter 34.4 is the sanity check; fix upstream
A demand forecast that ignores stock-outs	Demand is estimated as though supply were unconstrained	Chapter 24. Read the stock-out months beside the utilisation table
An epidemic curve with no engine named	The compartmental models are uncalibrated (HL-03)	Say which engine produced it; the endemic path is the default
Travel times that are too optimistic	Great-circle fallback where the road network is absent (HL-04)	Report the share of routed origin-destination pairs
An optimisation recommendation with no objective stated	Four objectives give four answers	Chapter 26. The objective is the most important assumption

38.4 Errors of interpretation and operation

Table 174: Errors of interpretation and operation

Symptom	Cause	Fix
An odds ratio quoted as 'times more likely'	The scale was not converted	Chapter 34.2. Report the marginal effect alongside
A synthetic figure quoted as evidence	The SYNTHETIC label was dropped	Automatic fail. Every Part III and IV figure carries it
A smoothed map read as data	Shrinkage and exceedance omitted	Chapter 17. Publish γ and P($\theta > \tau$)
A combined scenario reported as the sum of its parts	The interaction row was not read	Chapter 30.4
`using` fails on this host	An Application-Control policy blocks native package images	Pass `--pkgimages=no` on every julia invocation
A model reports `skipped_missing_variables`	The survey does not carry a required variable	That is the answer. Read the message; do not substitute a proxy silently

38.5 The postnatal-check diagnosis, worked

Chapter 6 flagged a continuation of 4.8 % at the postnatal step. This is how to decide whether a number like that is a finding or a fault.

1. Check the universe. Which women were asked the postnatal question, and does the denominator match? The at-risk count is 4,923.
2. Check the recall window and the timing condition. A 'check within two days of delivery' question is much narrower than 'any postnatal contact'.
3. Check the source variables in the indicator dictionary against the recode manual for this round.
4. Compare with the published national figure for the same round. A definition mismatch shows up immediately.
5. Compare with the second survey. A structural fault reproduces; a real collapse in one country does not.
6. Only then decide whether to report it, and report the diagnosis alongside.

WHY THIS IS IN THE MANUAL RATHER THAN FIXED QUIETLY

The number is what the run produced. Editing it out would leave the next analyst to rediscover it and would break the rule that a report reads the outputs rather than recomputing them. It is registered as HL-06, and the assessment asks for the diagnosis rather than the number.

Part VII — Governance

Disclosure control, reproducibility and audit, and the review questions.

39. Disclosure control and privacy

Every rule here has a line of code behind it that will stop a run.

39.1 The denominator threshold

No cell is published whose **unweighted** denominator falls below the threshold — 25 by default, set in `disclosure_control.yml`. The denominator is retained so that the suppression is visible.

UNWEIGHTED, NOT WEIGHTED

A weighted denominator can look comfortable while resting on three respondents with large weights. Disclosure risk attaches to the people, not to their weights.

39.2 Secondary suppression, and the third rule

Table 175: The three suppression rules

Situation	Action
One cell below threshold	Suppress it, and suppress the next smallest as secondary — otherwise the first is recoverable from the total
Two or more below threshold	Suppress all of them; no secondary is needed
A proportion of exactly 0 or 1 on a small denominator	Suppress — it identifies every respondent in the cell
A disclosed cell	Publish estimate, interval, denominator and the flag

39.3 Two real examples

Both are in `08_Data/indicators_uganda.csv`. The first is textbook secondary suppression.

SECONDARY SUPPRESSION, AS SHIPPED

```
indicator,dimension,level,estimate,...,n_unweighted,disclosed
malaria_rdt,education,primary,,...,14,false
malaria_rdt,education,none,,...,4782,false
```

`primary` has an unweighted denominator of 14 and fails the threshold. `none` has 4,782 and passes it — and is suppressed anyway, because this dimension has only two levels and the total minus `none` would return `primary` exactly.

TWO SUPPRESSED CELLS, BOTH ABOVE THE THRESHOLD

```
zero_dose,region,kigezi,,...,34,false
zero_dose,region,ankole,0.0277,...,45,true
zero_dose,region,kampala,0.0417,...,47,true
zero_dose,region,bugisu,,...,49,false
```

```
zero_dose,region,acholi,0.0105,...,53,true
```

Fifteen regions; two suppressed. Neither is below the threshold, and cells between them are disclosed.

WORK OUT WHICH RULE FIRED

It is not the denominator threshold: both cells clear it, and smaller cells beside them are disclosed. It is not ordinary secondary suppression either, which removes the next smallest cell. The third rule is the candidate: a degenerate proportion — exactly 0 or exactly 1 — on a small denominator is suppressed because it identifies every respondent in the cell. Zero-dose prevalence is around 5.5 % nationally, so a region with fifty children can easily contain none at all. That is the explanation the pattern supports; the suppressed file cannot confirm it, and this course does not assert what it cannot check.

39.4 Coordinates and restricted modules

- No coordinate leaves the estate — `assert_safe_output` raises if a latitude or longitude column reaches an output frame, and the security audit re-checks every file before shipping.
- Spatial covariates come from buffers — at least as large as the displacement radius — 2 km urban, 5 km rural, 10 km for the displaced one per cent.
- Facility registers are different — OpenStreetMap and ministry facility locations are public infrastructure, not respondents. That is why Chapter 25 can map points and Chapter 17 cannot.
- Restricted modules need two things — The HIV/biomarker module and the domestic-violence module require both a configuration flag and a recorded ethics approval reference. A flag alone is not sufficient, and this is the only place in the estate where that is true.

39.5 What a learner may publish in this course

NOTHING HERE CAN BE DISCLOSED

Every laboratory runs on committed outputs that already passed disclosure control, on the synthetic health-system run, and on public geographic layers. There is nothing a learner could leak. That is deliberate — but the habits are the point, and every laboratory deliverable is marked on whether the disclosure status was stated.

40. Reproducibility, provenance and audit

40.1 What makes a result reproducible

- Fixed seeds — every stochastic step — bootstrap, cross-validation folds, imputation draws, the Pareto sweep — is seeded

- Locked environments — `Manifest.toml` for Julia and `renv.lock` for R pin every dependency
- A configuration digest — recorded in every output's `.meta.json`. Two runs with the same digest saw the same configuration. The committed one is `6f173f8de3c0eddf`
- Shared identifiers — scenario_id, geo_id, year, unit registry, data_version, run_id and model_version are common across every EDIS sector system
- Source hashes — the run manifest records a hash of every input file, so a changed source is detectable without reading it

outputs/cross_sector/dhs_to_agriculture_Kenya_KE2022DHS.csv.meta.json


```
config_digest:  e0a07914179c04fd
generated_utc:  2026-08-05T09:32:40.388
output:  dhs_to_agriculture_Kenya_KE2022DHS.csv
model:  export_agriculture
system:  EDIS_DHS_Health_System
julia_version:  1.12.6
version:  1.0.0
country:  Kenya
disclosure_threshold:  25
survey:  KE2022DHS
kind:  estimates
rows:  470
```


One of 367 provenance sidecars written by the committed run.

40.2 The two audits

Table 176: Both are scripts, not checklists

Audit	What it verifies
`make audit`	registry fields present; controlled vocabularies respected; no duplicate identifiers; a declared identification strategy for every causal model; a validation design for every predictive model; and no model marked implemented whose function is not exported
`make security-audit`	staging empty; no identifier or coordinate column in any output; every disclosed cell above threshold; every estimate carrying uncertainty; every output with a sidecar

40.3 Validation on a known generating process

The test suite runs on synthetic fixtures generated from a known process, so the tests assert that estimators recover the true parameters rather than merely reproducing themselves — including the synthetic average treatment effect of 0.12, which the causal module's interval covers. A test suite that only checks self-consistency will pass on a systematically biased estimator.

40.4 Reproducing anything in this course

REPRODUCING THIS COURSE

```
# 1.  regenerate the extract from the model's committed outputs
cd D:/EDIP/Training/EDIS_Academy/_build
python health_extract.py # -> health_tables.json

# 2.  regenerate every figure and map
python health_figures.py # -> figures_hlt501/

# 3.  rebuild the course
python build_hlt501.py

# 4.  measure the rendered artefacts
python render_check.py -json \
  "../05_Sector_Planning/Health/HLT_501_Health_Sector_Modelling"
```

If the model's outputs change, step 1 changes every number and step 2 redraws every figure. The course cannot drift from the model without the build saying so.

41. Review questions

Answers in Appendix H. The final assessment is drawn from these.

Part I — the estate and its data

1. Name the four layers of the estate and say what kind of evidence each carries.
2. A colleague estimates infant mortality from the children's recode. What population have they described, and in which direction is the error?
3. Give two questions a household survey answers well and two it cannot answer at all.
4. The catalogue reports 36 skipped cards on the pilot survey. Is that a failure of the system? Justify your answer.
5. What are the four fields every published survey cell carries, and what does each protect against?
6. Why can Chapter 25 map facility points when Chapter 17 cannot map survey clusters?
7. An indicator has n = 10,000 and a design effect of 2.2. What is the effective sample size, and by what factor is the naive interval too narrow?

Part II — the population-health domains

1. Why is the complementary log-log link not a free choice in the mortality model?
2. Four maternal cards report four different percentages. Why is a direct comparison illegitimate?

3. What does a count model of children ever born estimate without an exposure offset?
4. State the proportional-odds assumption and describe how the system tests it.
5. Why does collapsing contraceptive method to 'modern versus not' matter for a commodity forecast?
6. A cascade step reports about five per cent continuation. Give four checks before reporting it.
7. A proportional change in variance is negative. What does that mean, and what must not be claimed?
8. Why does a bounded outcome need the Erreygers correction?
9. A shrinkage weight is 0.35. How much of the published estimate is model, and what must the table show?
10. The decision curve shows treat-all beating the model at every threshold. What is the correct output?

Part III — the health-system engine

1. Why does the engine project an age structure rather than a population total?
2. Write the effective reproduction number and say what makes an epidemic turn over.
3. Which epidemiology engine produced the case counts in this manual, and why does it matter that you say so?
4. Distinguish need, demand and utilisation, and give the equation that connects the first two.
5. Why does effective capacity differ from nominal capacity, and what are the three things that constrain it?
6. A service is overloaded while the register shows ample capacity. Explain.
7. What does the WISN requirement inherit from the demand model?
8. Why is a workforce gap not a vacancy count?
9. What does the safety-stock formula do when the service level moves from 90 to 99 per cent, and who should decide that?

Part IV — geography, optimisation and value

1. Why is nearest-facility distance the wrong default measure of access?
2. Write the two steps of the enhanced two-stage floating catchment and say what the first step divides by.
3. Which travel times in this estate are routed and which are great-circle, and why does it matter?
4. Name the five objectives of the facility-planning programme and say who asks for each.
5. What must a solver report carry besides the recommendation?
6. An equity floor is infeasible at the given budget. What should the model report?
7. Name three quantities in the costing chain that are external parameters rather than estimates.
8. State the WHO-CHOICE cost-effectiveness thresholds.
9. Which three reference parameters carry a DALY comparison across diseases?
10. Why can warming reduce malaria suitability in some places?

Parts V to VII — distribution, integration and governance

1. State the two definitions of catastrophic health spending and say which the estate publishes.
2. Why are raking weights trimmed, and what happens if calibration does not converge inside the trim?
3. A combined scenario reports zero change while a component reports a reduction. What has happened and what do you report?
4. Why does the macro export refuse to attach a currency value?
5. The transport export was skipped. What would activate it?
6. Why is the disclosure threshold applied to the unweighted denominator?
7. Explain secondary suppression with an example, and name the third suppression rule.
8. What does a configuration digest establish, and what does it not?
9. Name the four levels of validation and say which this estate does not have.

10. List the seven automatic fails and, for each, the chapter that explains it.

Appendices

Glossary; the model catalogue and the full card register; the equation register; notation, configuration and commands; answers; references; the twelve registered limitations; every committed estimate; and the estate module by module.

Appendix A. Glossary

Table 177: Glossary

Term	Meaning
2SFCA	Two-stage floating catchment area — an accessibility measure that divides facility capacity by the population that can reach it before summing over facilities.
AWT	Available working time: contracted hours net of absence, in minutes, used by the WISN requirement.
BR	The birth recode — one row per birth, alive or dead. The only correct source for mortality.
Catastrophic spending	Out-of-pocket health payments above a threshold share of consumption or of capacity to pay.
Cohort component	A population projection that ages each age-sex group forward with its own survival, then adds births and net migration.
DALY	Disability-adjusted life year: years of life lost plus years lived with disability.
deff	Design effect — the ratio of the design-based variance to the simple-random-sample variance at the same n.
Displacement	The deliberate offsetting of survey cluster coordinates before release: 2 km urban, 5 km rural, 10 km for one per cent of rural clusters.
EBLUP	Empirical best linear unbiased predictor — the Fay–Herriot small-area estimate.
Effective capacity	Nominal capacity constrained by staffing, readiness and opening hours.
Endemic engine	The incidence-driven default disease model, as opposed to the compartmental SIR and SEIR.
EOQ	Economic order quantity — the order size that minimises ordering plus holding cost.
Erlang-C	The probability that an arrival must wait, given servers and offered load.
Erreygers index	A mirror-invariant correction to the concentration index for a bounded outcome.
Fay–Herriot	An area-level small-area model that shrinks a direct estimate towards a regression prediction.
Gravity access	Capacity discounted by a power of travel time, summed over facilities.
Huff probability	The share of demand an origin sends to a facility, proportional to discounted capacity.
ICC	Intraclass correlation — the share of total variance that is between clusters.
ICER	Incremental cost-effectiveness ratio: change in cost divided by DALYs averted.
Kakwani index	Progressivity of health payments: the concentration index of payments minus the Gini of ability to pay.
KR	The children's recode — living children under five. Not a mortality file.
MMT	Minimum-mortality temperature — the bottom of the heat-mortality J-curve, 22 °C in this implementation.
MOR	Median odds ratio — the between-cluster variance restated on the odds scale.
Need / demand / utilisation	Epidemiological requirement; behavioural presentation; what capacity actually delivered. Three different quantities.
Nominal capacity	What a facility register says a facility can deliver, before any constraint.
PAF	Population attributable fraction — the share of burden attributable to a risk factor.
PCV	Proportional change in variance — the share of cluster variance a covariate set explains. Can be negative.
Provenance tag	observed, estimated, imputed, projected, scenario or synthetic — carried by every datum.

continued on the next page

Rao–Scott	A first-order correction to the chi-squared statistic for a complex design.
R_0 and R_t	Basic and effective reproduction numbers; R_t = (β/γ)(S/N).
Safety stock	Buffer inventory sized by the service level and the variability of demand and lead time.
Shrinkage weight γ	The weight a small-area model gives the area's own direct estimate; $1-\gamma$ is the model's share.
(s,S) policy	Order up to S whenever on-hand stock falls to the reorder point s.
Secondary suppression	Suppressing a second cell so the first cannot be recovered from the total.
Theil-T	An inequality index used here on the accessibility distribution, population-weighted.
WISN	Workload Indicators of Staffing Need — the WHO method for deriving staff requirements from service workload.
YLL / YLD	Years of life lost to premature death; years lived with disability.
Zero-dose child	A child who has received no dose of any routine vaccine.
Zero-shock test	Running a microsimulation with every lever at baseline; it must reproduce the baseline.

Appendix B. The model catalogue

All 97 population-health cards, with what each committed run did with them. The status columns are read from the catalogue summaries; nothing here is transcribed.

B.1 Completion by family and estimator

Table 178: Completion by family and estimator

Family	Cards	Uganda	Kenya
prediction bridge	12	5	5
child nutrition	9	7	6
maternal health	8	8	8
fertility fp	8	5	5
inequality causal	8	6	6
multilevel spatial	7	2	2
child survival	7	6	6
child morbidity	6	3	3
immunization	6	5	4
wash env	6	6	6
malaria hiv	6	1	0
maternal nutrition	5	5	3
empowerment gender	5	0	0
insurance access	4	2	1
Total	97	61	55

Table 179: Completion by estimator, Uganda 2016

Estimator	Cards	Complete	Skipped
logit	71	38	33
count	5	5	0
ordinal	4	3	1
quantile	4	3	1
multinomial	3	2	1
multilevel	1	1	0
concentration	1	1	0
erreygers	1	1	0
fairlie	1	1	0
cge_bridge	1	1	0
microsim	1	1	0
oaxaca	1	1	0
causal	1	1	0
variance_components	1	1	0
wagstaff	1	1	0

B.2 Every card, with its run status

Table 180: The 97 cards

#	Model	Family	Outcome	UGA	KEN	n
1	Neonatal mortality probability	A	death within 0–27 days	yes	yes	11,667
2	Post-neonatal mortality	A	death 1–11 months	yes	yes	50,555
3	Infant mortality survival	A	time to death before age 1	yes	yes	39,701
4	Under-five mortality survival	A	time to death before age 5	yes	yes	615
5	Competing-risk child mortality	A	cause/state-specific child exit where cause data exist	no	no	—
6	Birth-interval mortality model	A	effect of preceding interval on mortality	yes	yes	32,027
7	High-risk fertility mortality model	A	joint demographic risk score and mortality	yes	yes	32,027
8	Adequate ANC model	B	probability of adequate antenatal contacts	yes	yes	10,219
9	Early ANC initiation	B	first ANC in first trimester	yes	yes	10,019
10	Number of ANC contacts	B	ANC visit count	yes	yes	10,219
11	Skilled birth attendance	B	skilled attendant at delivery	yes	yes	15,522
12	Facility delivery	B	delivery in health facility	yes	yes	15,522
13	Caesarean delivery	B	C-section probability	yes	yes	15,460
14	Postnatal care	B	timely postnatal check	yes	yes	10,219
15	Maternal continuum completion	B	ANC→facility/SBA→PNC completion	yes	yes	10,219
16	Children ever born	C	lifetime/parity count	yes	yes	18,506
17	Recent fertility	C	birth in reference period	no	no	—
18	Birth spacing hazard	C	time to next birth	yes	yes	23,778
19	Modern contraceptive use	C	current modern method use	yes	yes	11,379
20	Contraceptive method choice	C	choice among method categories	yes	yes	11,379
21	Unmet need model	C	unmet need for family planning	yes	yes	11,379
22	Demand satisfied model	C	demand for FP satisfied by modern methods	no	no	—
23	Fertility preference mismatch	C	partner/woman preference disagreement	no	no	—
24	Stunting probability	D	height-for-age z<-2	yes	yes	4,423
25	Severe stunting	D	HAZ<-3	yes	yes	4,423
26	Wasting probability	D	weight-for-height z<-2	yes	yes	4,413
27	Underweight probability	D	weight-for-age z<-2	yes	yes	4,441
28	Continuous HAZ model	D	height-for-age z score	yes	yes	4,423
29	Continuous WHZ model	D	weight-for-height z score	yes	yes	4,413
30	Minimum dietary diversity	D	child meets MDD	no	no	—
31	Minimum acceptable diet	D	child meets MAD	no	no	—
32	Child anaemia severity	D	none/mild/moderate/severe	yes	no	3,944
33	Women's BMI model	E	continuous BMI	yes	yes	6,049
34	Women's underweight	E	BMI<18.5	yes	yes	6,049
35	Women's overweight/obesity	E	BMI≥25/30	yes	yes	6,049
36	Women's anaemia	E	anaemia status	yes	no	6,031
37	Anaemia severity ordered model	E	severity category	yes	no	6,031
38	Fever prevalence	F	recent fever	yes	yes	4,527

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continued

#	Model	Family	Outcome	UGA	KEN	n
39	ARI symptoms	F	acute respiratory infection symptoms	yes	yes	4,527
40	Diarrhoea prevalence	F	recent diarrhoea	yes	yes	4,523
41	Care seeking for fever/ARI	F	care sought from appropriate provider	no	no	—
42	ORS treatment	F	ORS for diarrhoea	no	no	—
43	Appropriate fever treatment	F	appropriate antimalarial where measurable	no	no	—
44	Full basic immunization	G	child fully immunized	yes	yes	953
45	Zero-dose child model	G	no DTP-containing dose	yes	yes	953
46	DTP dropout	G	DTP1 to DTP3 dropout	yes	yes	907
47	Measles vaccination	G	measles-containing vaccine receipt	yes	yes	953
48	Vaccination timeliness	G	age at vaccine receipt	no	no	—
49	Bednet use by child	G	slept under ITN	yes	no	4,796
50	Malaria parasitaemia	H	positive malaria test where available	yes	no	4,796
51	Malaria anaemia joint-risk	H	anaemia conditional on malaria status	no	no	—
52	HIV prevalence	H	HIV positive where biomarker available	no	no	—
53	HIV testing uptake	H	ever/recently tested	no	no	—
54	Comprehensive HIV knowledge	H	knowledge indicator	no	no	—
55	HIV stigma attitude model	H	stigma index/category	no	no	—
56	Improved drinking water	I	household has improved source	yes	yes	19,588
57	Improved sanitation	I	improved sanitation	yes	yes	19,588
58	Open defecation	I	household practices open defecation	yes	yes	19,588
59	Clean cooking transition	I	clean versus polluting fuel	yes	yes	19,588
60	Household environmental health index	I	latent/indexed environmental deprivation	yes	yes	19,588
61	WASH–diarrhoea association	I	child diarrhoea conditional on WASH	yes	yes	4,523
62	Household decision-making index	J	latent empowerment score	no	no	—
63	Empowerment and maternal care	J	maternal service use conditional on empowerment	no	no	—
64	Employment and reproductive health	J	modern contraception/ANC by employment	no	no	—
65	Intimate partner violence risk	J	IPV indicator where DV module available	no	no	—
66	IPV and health-service use	J	service use conditional on IPV exposure	no	no	—
67	Health insurance coverage	K	insured indicator	yes	no	18,506
68	Reported access barriers	K	any serious barrier to care	no	no	—
69	Provider choice for child illness	K	public/private/pharmacy/other/no care	no	no	—
70	Facility delivery choice	K	public/private/home/other	yes	yes	15,522
71	Concentration index for health outcome	L	socioeconomic inequality in y	yes	yes	4,423
72	Erreygers corrected concentration index	L	inequality for bounded binary outcomes	yes	yes	4,423
73	Wagstaff decomposition	L	contributions to health inequality	yes	yes	4,423
74	Oaxaca-Blinder health-gap decomposition	L	group gap in continuous outcome	yes	yes	4,423
75	Fairlie decomposition	L	group gap in binary outcome	yes	yes	4,423
76	Propensity-score treatment effect	L	effect of observable treatment/exposure	yes	yes	4,423
77	Instrumental-variable health model	L	causal effect where valid instrument exists	no	no	—
78	Difference-in-differences with repeated DHS	L	policy effect across rounds/areas	no	no	—
79	Cluster random-intercept health model	M	health outcome with community heterogeneity	yes	yes	4,423
80	Region/district hierarchical model	M	outcome with higher-level heterogeneity	yes	yes	4,423
81	Spatial Gaussian process prevalence model	M	continuous spatial risk surface	no	no	—
82	Bayesian small-area prevalence	M	area prevalence borrowing strength	no	no	—
83	Unit-level small-area model	M	individual DHS outcome plus census covariates	no	no	—
84	Spatially varying coefficient model	M	effect heterogeneity over space	no	no	—
85	DHS cluster accessibility-health model	M	health outcome linked to modeled facility travel time	no	no	—
86	Random-forest health-risk model	N	predict selected DHS health outcome	no	no	—
87	Gradient-boosted health-risk model	N	predict selected outcome	no	no	—
88	Super learner/stacked ensemble	N	combine candidate predictive models	no	no	—
89	DHS health vulnerability index	N	multidimensional household/individual vulnerability	yes	yes	19,588
90	Household health microsimulation	N	simulate policy-induced probability changes	yes	yes	4,423
91	Maternal-child intervention microsimulation	N	jointly simulate ANC/SBA/PNC and child outcomes	no	no	—
92	Climate-health DHS bridge	N	translate climate exposures into health-risk shifts	no	no	—
93	Agriculture-nutrition DHS bridge	N	translate food/agricultural shocks into nutrition outcomes	no	no	—

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continued

#	Model	Family	Outcome	UGA	KEN	n
94	Education-health DHS bridge	N	estimate health returns to maternal/ household education	yes	yes	4,423
95	Health-to-labour productivity bridge	N	map DHS morbidity/nutrition states to productivity parameters	no	no	—
96	Health-to-household/CGE bridge	N	map health indicators to representative households/factors	yes	yes	4,423
97	Health policy targeting score	N	rank households/areas by expected benefit or risk	yes	yes	4,423

B.3 Why cards were skipped, verbatim

Table 181: The 36 skip reasons, Uganda 2016

Model	Reason the run gave
agriculture_nutrition_dhs_bridge	not wired on this platform: requires food-security / agricultural exposure proxies not collected in standard DHS
appropriate_fever_treatment	not wired on this platform: needs an antimalarial (ml13*) treatment conditional cohort — not yet built
bayesian_small_area_prevalence	not wired on this platform: area-level SAE is implemented via SmallAreaEstimation.jl (Fay-Herriot) + run_africa_sae_forecast.jl — operates on aggregated regional inputs, not a per-model unit run
care_seeking_for_fever_ari	not wired on this platform: needs a care-seeking outcome (h32*) conditional cohort — not yet built
climate_health_dhs_bridge	not wired on this platform: requires cluster-matched climate exposure (CHIRPS/temperature rasters) — blocked by the GDAL/SAC raster wall on this host
competing_risk_child_mortality	required DHS variable(s) ["b_cause_of_death"] absent from the BR recode; no substitute used
comprehensive_hiv_knowledge	not wired on this platform: needs an HIV-knowledge composite cohort (v754*/v756) — not yet built
demand_satisfied	not wired on this platform: needs a demand-satisfied composite (use ÷ (use+unmet)) cohort column
dhs_cluster_accessibility_health_model	not wired on this platform: requires cluster travel-time (GE GPS + facility register) merged to the outcome cohort — travel time computed by run_gis_access.jl; merge-to-outcome not yet wired
difference_in_differences_with_repeated_dhs	not wired on this platform: requires harmonised repeated rounds + policy timing — available via Causal.jl DiD on pooled multi-round data, not a single-survey run
employment_and_reproductive_health	not wired on this platform: needs an employment (v714/v731) covariate cohort — not yet built
empowerment_and_maternal_care	not wired on this platform: needs empowerment score merged to maternal-care outcomes — not yet built
fertility_preference_mismatch	not wired on this platform: needs the Couples recode (CR) and a couple-linked preference cohort
gradient_boosted_health_risk_model	not wired on this platform: gradient boosting runs via Prediction.jl/ gradient_boost with grouped-CV tuning + SHAP — dedicated ML pipeline
health_to_labour_productivity_bridge	not wired on this platform: calibration bridge to CDCGE factor productivity — implemented via CrossSectorExports.jl (health→macro), needs literature elasticities not a per-cohort fit
hiv_prevalence	recode AR not found
hiv_stigma_attitude_model	not wired on this platform: needs an HIV-stigma scale cohort (v857*) — not yet built
hiv_testing_uptake	not wired on this platform: needs an HIV-testing cohort (v781/v826) — not yet built
household_decision_making_index	not wired on this platform: needs an empowerment-score (v743*) index cohort — not yet built

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Model	Reason the run gave
instrumental_variable_health_model	not wired on this platform: requires a credible instrument (identification review) — Causal.jl IV template refuses by default on standard DHS
intimate_partner_violence_risk	not wired on this platform: needs the DV-module (d105*) subsample cohort with DV weights — not yet built
ipv_and_health_service_use	not wired on this platform: needs DV module merged to service-use outcomes — not yet built
malaria_anaemia_joint_risk	not wired on this platform: needs a merged malaria+anaemia biomarker cohort (hml32+hml35+hc57/ha57) — not yet built
maternal_child_intervention_microsimulation	not wired on this platform: sequential cascade microsimulation across linked cards — orchestrated via run_extended.jl scenarios, not a single-cohort run
minimum_acceptable_diet	not wired on this platform: needs an IYCF feeding-frequency + diversity cohort — not yet built
minimum_dietary_diversity	not wired on this platform: needs an IYCF food-group cohort (v409–v414/v410–v414) — not yet built
ors_treatment	not wired on this platform: needs an ORS (h13) treatment conditional cohort — not yet built
provider_choice_for_child_illness	not wired on this platform: needs a treatment-source (h32*) multinomial cohort — not yet built
random_forest_health_risk_model	not wired on this platform: random-forest risk models run via Prediction.jl/ml_predict (grouped-CV AUROC/Brier/calibration) as a dedicated ML pipeline, not the design-based per-model engine
recent_fertility	not wired on this platform: needs a recent-birth (v208-derived) binary cohort builder
reported_access_barriers	not wired on this platform: needs a big-problem access-barrier cohort (v467b–v467f) — not yet built
spatial_gaussian_process_prevalence_model	not wired on this platform: requires Bayesian geostatistics (R-INLA/SPDE) — native BYM/CAR available via SpatialModels.jl + run_spatial_adjacency.jl
spatially_varying_coefficient_model	not wired on this platform: requires Bayesian spatially-varying coefficients (R-INLA/SPDE) — not on this host
super_learner_stacked_ensemble	not wired on this platform: cross-validated stacking of base learners — not yet wired (base learners available via Prediction.jl)
unit_level_small_area_model	not wired on this platform: requires harmonised census/satellite auxiliary covariates not present in this cache
vaccination_timeliness	not wired on this platform: needs a vaccination-date event-history cohort (h3d/h5d/h9d) — not yet built

B.4 The implementing files

Table 182: `src/Models/<family>/` — one Julia file per card

Family	Files
child morbidity	appropriate_fever_treatment, ari_symptoms, care_seeking_for_fever_ari, diarrhoea_prevalence, fever_prevalence, ors_treatment
child nutrition	child_anaemia_severity, continuous_haz, continuous_whz_model, minimum_acceptable_diet, minimum_dietary_diversity, severe_stunting, stunting_probability, underweight_probability, wasting_probability
child survival	birth_interval_mortality_model, competing_risk_child_mortality, high_risk_fertility_mortality_model, infant_mortality_survival, neonatal_mortality_probability, post_neonatal_mortality, under_five_mortality_survival
empowerment gender	employment_and_reproductive_health, empowerment_and_maternal_care, household_decision_making_index, intimate_partner_violence_risk, ipv_and_health_service_use
fertility fp	birth_spacing_interval, children_ever_born, contraceptive_method_choice, demand_satisfied, fertility_preference_mismatch, modern_contraceptive_use, recent_fertility, unmet_need
immunization	bednet_use_child, dtp_dropout, full_basic_immunization, measles_vaccination, vaccination_timeliness, zero_dose_child_model
inequality causal	concentration_index_for_health_outcome, difference_in_differences_with_repeated_dhs, erreygers_corrected_concentration_index, fairlie_decomposition, instrumental_variable_health_model, oaxaca_blinder_health_gap_decomposition, propensity_score_treatment_effect, wagstaff_decomposition
insurance access	facility_delivery_choice, health_insurance_coverage, provider_choice_for_child_illness, reported_access_barriers
malaria hiv	comprehensive_hiv_knowledge, hiv_prevalence, hiv_stigma_attitude_model, hiv_testing_uptake, malaria_anaemia_joint_risk, malaria_parasitaemia
maternal health	adequate_anc_model, caesarean_delivery, early_anc_initiation, facility_delivery, maternal_continuum_completion, number_of_anc_contacts, postnatal_care, skilled_birth_attendance
maternal nutrition	anaemia_severity_ordered_model, womens_anaemia, womens_bmi_model, womens_overweight_obesity, womens_underweight
multilevel spatial	bayesian_small_area_prevalence, cluster_random_intercept_health_model, dhs_cluster_accessibility_health_model, region_district_hierarchical_model, spatial_gaussian_process_prevalence_model, spatially_varying_coefficient_model, unit_level_small_area_model
prediction bridge	agriculture_nutrition_dhs_bridge, climate_health_dhs_bridge, dhs_health_vulnerability_index, education_health_dhs_bridge, gradient_boosted_health_risk_model, health_policy_targeting_score, health_to_household_cge_bridge, health_to_labour_productivity_bridge, household_health_microsimulation, maternal_child_intervention_microsimulation, random_forest_health_risk_model, super_learner_stacked_ensemble
wash env	clean_cooking_transition, household_environmental_health_index, improved_drinking_water, improved_sanitation, open_defecation, wash_diarrhoea_association

Appendix C. The equation register

72 stable identifiers across 16 sections of `HEALTH_MODELS_AND_EQUATIONS.md`. An identifier never changes meaning, so a report can cite one and stay correct across model versions.

Table 183: The sections

Section	Block
0	Preliminaries
1	Demography — cohort-component projection
2	Epidemiology & disease burden
3	Service demand
4	Facility capacity, utilization & queueing
5	Geographic accessibility (GIS)
6	Health workforce
7	Medicine supply chain
8	Health financing, costing & value
9	Health outcomes — GBD DALYs
10	Optimization models (JuMP / HiGHS · Ipopt · PATHSolver)
11	Poverty, welfare & distribution
12	Climate–health risk
13	Macroeconomic / CGE integration
14	Statistical & reference tables
15	Outputs

Table 184: Every equation identifier, and where this manual covers it

ID	What it computes	Function	Chapter
H-D-01	Survival & aging		20
H-D-02	Fertility & births		20
H-D-03	Migration		20
H-D-04	Dependency ratio		20
H-E-01	SIR	`sir_step`	20
H-E-02	SEIR	`seir_step`	20
H-E-03	Endemic (default engine)		20
H-E-04	Climate multiplier	`climate_multiplier`	20
H-E-05	Prevention / vaccination	`prevention_factor`	20
H-E-06	Seasonal forcing	`seasonal_beta`	20
H-E-07	Effective reproduction number	`reproduction_number`	20
H-E-08	Age-structured SEIR	`simulate_age_seir`	20
H-E-09	Basic reproduction number	`basic_reproduction_number`	20
H-E-10	Population attributable fraction	`attributable_fraction`	20
H-S-01	Need		21
H-S-02	Adjusted demand		21
H-S-03	Price elasticity of demand	`demand_price_factor`	21
H-C-01	Staffing capacity		22
H-C-02	Effective capacity		22
H-C-03	Utilization / served / unmet		22
H-C-04	Queueing wait probability		22
H-C-05	Bed occupancy	`bed_occupancy`	22
H-A-01	Distance & travel time		25
H-A-02	Threshold coverage		25
H-A-03	Gravity accessibility		25
H-A-04	Enhanced 2SFCA	`compute_2sfca`	25
H-A-05	Three-step FCA	`compute_3sfca`	25
H-A-06	Huff choice probability	`huff_probabilities`	25
H-A-07	Underserved gap score	`identify_underserved_areas`	25
H-A-08	Access inequality		25
H-W-01	WISN requirement		23
H-W-02	Staffing input & stock	`cadre_multiplier`	23
H-W-03	Stock-flow projection	`project_workforce`	23
H-W-04	Gap & density		23
H-W-05	Training pipeline	`training_pipeline`	23
H-W-06	Skill mix		23
H-SC-01	Inventory balance	`stock_projection`	24
H-SC-02	Service-level safety stock	`safety_stock`	24
H-SC-03	EOQ	`eoq`	24
H-SC-04	s,S) policy		24
H-SC-05	Commodity requirement	`commodity_requirement`	24
H-F-01	Service cost		27

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ID	What it computes	Function	Chapter
H-F-02	Financing envelope	`financing_envelope`	27
H-F-03	Required expenditure & gap	`financing_summary`	27
H-F-04	Bottom-up input costing	`input_costing`	27
H-F-05	Cost-effectiveness	`cost_effectiveness`	27
H-F-06	Fiscal space	`fiscal_space`	27
H-O-01	Deaths with treatment		28
H-O-02	Years of life lost		28
H-O-03	Years lived with disability		28
H-O-04	DALYs & averted		28
H-OPT-01	Facility planning MILP	`plan_facilities`	26
H-OPT-02	Workforce allocation MIP	`optimize_workforce_allocation`	26
H-OPT-03	Referral network LP	`optimize_referral_network`	26
H-OPT-04	Supply distribution LP	`optimize_supply_distribution`	26
H-P-01	OOP after policy	`apply_health_policy`	30
H-P-02	Consumption after payment		30
H-P-03	Catastrophic — budget share		30
H-P-04	Catastrophic — WHO capacity-to-pay		30
H-P-05	Impoverishment		30
H-P-06	Poverty headcount / gap		30
H-P-07	Concentration index of OOP		30
H-P-08	Gini		30
H-CL-01	Heat–mortality exposure-response	`heat_mortality_rr`	29
H-CL-02	Malaria climate envelope	`malaria_suitability`	29
H-CL-03	Attributable climate burden	`climate_health_burden`	29
H-CL-04	Heat-attributable deaths	`heat_attributable_deaths`	29
H-CL-05	Facility exposure & resilience	`facility_climate_exposure`	29
H-M-01	Exchange objects		31
H-M-02	Iterative convergence	`iterate_health_macro`	31
H-M-03	CDCGE adapter	`read_cdcge_results`	31
H-M-04	Education linkage	`education_demand`	31

Appendix D. Notation

Table 185: Notation

Symbol	Meaning	Chapter
i, r, f, j	settlements, areas, facilities, candidate sites	19
a, x, d, k	age group, sex, disease, service	19
c, m, w, h	cadre, medicine, warehouse, household	19
t	year, base year to projection year	19
w_i	sample weight after division by 10^6	4
$\hat{R}$	weighted ratio estimator	4
m_h	primary sampling units in stratum h	4
deff, n_eff	design effect and effective sample size	4
σ_a, ω_a	age-specific survival and ageing-out rate	20
β, γ, σ, μ	transmission, recovery, incubation, mortality rates	20
CM, PF	climate multiplier and prevention factor	20
υ_k	visits per case for service k	21
ε	price elasticity of demand, 0.18	21
CAP[f,k]	effective capacity of facility f for service k	22
U, SERVED, UNMET	utilisation, served and unmet demand	22
T_{if}	travel time from origin i to facility f	25
g(T)	distance-decay weight exp($-\beta$T/τ)	25
R_j, A_i	supply ratio and accessibility score in 2SFCA	25
G_i	underserved gap score	25
AWT_c, σ_k, ψ_{c,k}	available working time, staff-minutes, cadre-service mix	23
SS, Q*, s, S	safety stock, EOQ, reorder point, order-up-to	24
REQ, FIN, GAP	required expenditure, financing envelope, gap	27
DW, LE, D(L,ρ)	disability weight, life expectancy, discounted life-years	28

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continued

Symbol	Meaning	Chapter
RR(T), S(T,rain)	heat relative risk, malaria suitability	29
open_j, x_{ij}, unmet_i	MILP siting variables	26
OOP_h, pw_h	out-of-pocket payment and person weight	30
γ_a, D_a	shrinkage weight and design variance in Fay–Herriot	17
ICC, MOR, PCV	multilevel variance summaries	16

Appendix E. Configuration, modules and data

E.1 Configuration files

- countries.yml
- covariates.yml
- cross_sector_links.yml
- disclosure_control.yml
- local_paths.example.yml
- local_paths.yml
- model_registry.yml
- outcomes.yml
- project.yml
- scenario.yml
- scenario_definitions.yml
- surveys.yml
- variables.yml

E.2 The module tree

Table 186: `src/API/` — 2 modules

Module	Lines
Routes.jl	197
app.jl	20
Total	217

Table 187: `src/Core/` — 6 modules

Module	Lines
Config.jl	187
DataSchema.jl	132
HealthTypes.jl	87
ScenarioManager.jl	49
Types.jl	35
Validation.jl	161
Total	651

Table 188: `src/Data/` — 3 modules

Module	Lines
Database.jl	97
HealthLoader.jl	80
Loader.jl	27
Total	204

Table 189: `src/GIS/` — 2 modules

Module	Lines
Accessibility.jl	443
ClimateRisk.jl	154
Total	597

Table 190: `src/Integration/` — 4 modules

Module	Lines
CDCGELink.jl	94
EducationLink.jl	60
MacroLink.jl	135
Poverty.jl	136
Total	425

Table 191: `src/Models/` — 14 modules

Module	Lines
Demand.jl	10
Demography.jl	3
DiseaseBurden.jl	400
Epidemiology.jl	18
FacilityCapacity.jl	122
Financing.jl	9
HealthFinancing.jl	236
Outcomes.jl	8
Population.jl	117
Reference.jl	90
Supply.jl	13
SupplyChainModel.jl	108
Workforce.jl	5
WorkforcePlanning.jl	190
Total	1,329

Table 192: `src/Optimization/` — 10 modules

Module	Lines
BudgetAllocation.jl	13
CostBenefit.jl	148
FacilityLocation.jl	18
FacilityPlanning.jl	189
ReferralNetwork.jl	11
ReferralOptimization.jl	66
SupplyChain.jl	17
SupplyDistribution.jl	61
WorkforceAllocation.jl	16
WorkforceOptimization.jl	62
Total	601

Table 193: `src/Results/` — 2 modules

Module	Lines
Indicators.jl	71
Reports.jl	95
Total	166

Table 194: `src/Services/` — 2 modules

Module	Lines
JobService.jl	73
ScenarioStore.jl	38
Total	111

Table 195: `src/Simulation/` — 3 modules

Module	Lines
DynamicEngine.jl	296
Engine.jl	41
HealthEngine.jl	151
Total	488

Table 196: `src/julia/` — the survey estimation core, 29 modules

Module	Lines
EDISDHSHealth.jl	144
CLI.jl	176
Causal.jl	404
Config.jl	236
CrossSectorExports.jl	577
DHSIngestion.jl	54
DataInventory.jl	189
DescriptiveAnalytics.jl	190
Explainability.jl	210
FeatureEngineering.jl	279
Forecasting.jl	202
GISAccessibility.jl	306
Harmonisation.jl	783
HealthSystemPlanning.jl	253
Inequality.jl	336
LatentIndex.jl	134
Microsimulation.jl	365
MissingData.jl	220
ModelCatalogue.jl	499
ModelRegistry.jl	245
Models.jl	643
Multilevel.jl	227
Optimisation.jl	218
Prediction.jl	320
Reporting.jl	199
SmallAreaEstimation.jl	60
SpatialModels.jl	184
SurveyDesign.jl	233
Validation.jl	381
Total	8,267

E.3 The health documentation set

Table 197: `docs/health/`

Document	Lines
ACCESSIBILITY_METHODS.md	43
ADMIN_GUIDE.md	45
API_REFERENCE.md	87
ARCHITECTURE.md	58
BUDGET_TO_SERVICES_TO_OUTPUTS_METHODOLOGY.md	338
CHANGELOG.md	156
CLIMATE_HEALTH.md	36
DATA_DICTIONARY.md	211
DEPLOYMENT.md	37
EPIDEMIOLOGY_MODELS.md	37
HEALTH_MODELS_AND_EQUATIONS.md	510
HEALTH_SYSTEM_MATHEMATICAL_SPECIFICATION.md	207
HEALTH_SYSTEM_VALIDATION_REPORT.md	55
IMPLEMENTATION_PLAN.md	70
LIMITATIONS.md	45
MACRO_CGE_INTEGRATION.md	37
MATHEMATICAL_SPECIFICATION.md	10
OPTIMIZATION_MODELS.md	43
POVERTY_MICROSIMULATION.md	35
README.md	50
USER_GUIDE.md	81

E.4 The geographic data estate

20 sources across 55 African countries at `D:/EDIP/data/Healthdata/africa-health-gis/data/raw`. The 'with data' column counts countries holding actual files rather than a placeholder instruction.

Table 198: What is registered, and what is present (HL-12)

Source	Countries registered	With data	Files
geoboundaries	54	54	210
osm health	54	54	105
osm roads	54	54	108
worldpop	54	54	108
who gho indicators	55	53	229
dhs indicators	42	42	84
grid3	12	11	49
chirps rainfall	1	1	14
hydrosheds	1	1	3
jrc surface water	1	1	45
malaria atlas	1	1	3
naturalearth	1	1	3
worldclim	1	1	3
copernicus landcover	55	0	158
dhs spatial	55	0	158
healthsites	54	0	157
moh master facility list	1	0	1
srtm elevation	55	0	158
viirs nightlights	1	0	1
who facilities	55	0	158

Table 199: The Uganda layers every map in this manual is drawn from

Source	File	Size
dhs indicators	dhs_indicators_UGA.json	57 KB
geoboundaries	UGA_ADM0.geojson	1,573 KB
geoboundaries	UGA_ADM1.geojson	1,723 KB
geoboundaries	UGA_ADM2.geojson	1,751 KB
geoboundaries	UGA_ADM3.geojson	537 KB
geoboundaries	UGA_ADM4.geojson	46,550 KB
osm health	osm_health_UGA.json	1,937 KB
who gho indicators	who_gho_UGA.json	502 KB
worldpop	uga_ppp_2020_UNadj.tif	97,665 KB

E.5 The optional R layer

- 00_setup.R
- 01_inventory.R
- 02_ingest_recode.R
- 03_harmonise.R
- 04_survey_design.R
- 05_descriptive.R
- 06_mortality_survival.R
- 07_maternal_health.R
- 08_fertility_family_planning.R
- 09_nutrition_anthropometry.R
- 10_anaemia_biomarkers.R
- 11_vaccination.R
- 12_disease_risk.R
- 13_empowerment_gender.R
- 14_inequality_decomposition.R
- 15_multilevel_models.R

- 16_spatial_models.R
- 17_small_area_estimation.R
- 18_causal_inference.R
- 19_machine_learning.R
- 20_forecasting.R
- 21_microsimulation_bridge.R
- 22_reporting.R
- 23_verify_real_data.R

Appendix F. Command quick reference

Table 200: Command quick reference

Task	Command
Instantiate	`julia --pkgimages=no --project=. -e 'using Pkg; Pkg.instantiate()'`
Run the test suite	`make test`
Full synthetic pipeline	`make e2e`
Print the plan, open nothing	`make dry-run COUNTRY=... SURVEY=...`
Cohorts and checks, no estimates	`make validate COUNTRY=... SURVEY=...`
The full survey run	`make country COUNTRY=... SURVEY=...`
One registered model	`make model MODEL=...`
List every registered model	`make models-list`
Registry and provenance audit	`make audit`
The refuse-to-ship gate	`make security-audit`
Render every report	`make report` / `make report-pdf`
Run the health-system engine	`julia --pkgimages=no --project=. -e 'using IntegratedHealthSystemModel; run_health_scenario(...)'`
Start the API and dashboard	`julia --project=. app.jl`
R capability report	`Rscript src/r/00_setup.R`
R against Julia on real data	`make r-verify`
Rebuild this course	`python health_extract.py && python health_figures.py && python build_hlt501.py`

`--PKGIMAGES=NO` IS MANDATORY ON THIS HOST

An Application-Control policy blocks native package images. The Makefile and every pipeline already pass the flag; a direct `julia` invocation must pass it too. The symptom of forgetting is a failure at `using`, before any of your code runs.

Appendix G. References

Authority levels: **L1-MODEL** implemented code or its committed output; **L1-DOC** the model's own documentation; **L2-LIT** published method literature; **L3-DATA** an external data product.

L1-MODEL

Table 201: L1-MODEL

Source	What it provides
EDIS Health Sector Decision Intelligence System	D:/EDIP/models/HealthModelling/src — 48 Julia modules across 10 layers, including 14 health-system models, 10 optimisation models, 2 GIS modules and 4 integration links
The population-health model implementations	97 per-card Julia files under `src/Models/`, one per catalogue card, organised by the 14 domain families
The DHS estimation core	29 modules (8,267 lines) under `src/julia/`, with 24 optional R scripts and 97 model configurations
Committed run outputs	613 CSV outputs with 367 provenance sidecars covering Uganda 2016 DHS (UG2016DHS) and Kenya 2022 DHS (KE2022DHS), plus the health-system run `run_ZAN_baseline_20260722175948` on Zandia (ZAN) — the health-system engine's SYNTHETIC demo country

L1-DOC

Table 202: L1-DOC

Source	What it provides
HEALTH_MODELS_AND_EQUATIONS.md	The consolidated equation reference: 72 stable equation identifiers across 16 sections, from demography to the CGE handover
EDIS DHS Health Modelling Technical Manual, EDIS, August 2026	97 model cards in 14 families, each with purpose, outcome, specification, inputs, estimator, design treatment, diagnostics, outputs, integration target, scenarios and implementation notes
The method notes	ACCESSIBILITY_METHODS, EPIDEMIOLOGY_MODELS, OPTIMIZATION_MODELS, MACRO_CGE_INTEGRATION, POVERTY_MICROSIMULATION, CLIMATE_HEALTH, BUDGET_TO_SERVICES_TO_OUTPUTS_METHODOLOGY, DATA_DICTIONARY
The system's own honesty documents	IMPLEMENTATION_STATUS.md, REMAINING_GAPS.md (14 registered items), TEST_RESULTS.md, LIMITATIONS.md, HEALTH_SYSTEM_VALIDATION_REPORT.md

L2-LIT

Table 203: L2-LIT

Source	What it provides
Rao, J.N.K. and Scott, A.J. (1984)	On chi-squared tests for multiway contingency tables with cell proportions estimated from survey data
Wagstaff, A., van Doorslaer, E. and Watanabe, N. (2003)	On decomposing the causes of health sector inequalities
Erreygers, G. (2009)	Correcting the concentration index
Fay, R.E. and Herriot, R.A. (1979)	Estimates of income for small places: an application of James–Stein procedures
Riebler, A., Sørbye, S.H., Simpson, D. and Rue, H. (2016)	An intuitive Bayesian spatial model for disease mapping that accounts for scaling (BYM2)
Luo, W. and Qi, Y. (2009)	An enhanced two-step floating catchment area method for measuring spatial accessibility to primary care physicians
Wan, N., Zou, B. and Sternberg, T. (2012)	A three-step floating catchment area method for analysing spatial access to health services
Huff, D.L. (1964)	Defining and estimating a trading area — the choice model the provider-choice card uses
World Health Organization (2010)	Workload indicators of staffing need (WISN): user's manual
Xu, K. et al. (2003)	Household catastrophic health expenditure: a multicountry analysis — the capacity-to-pay definition
Murray, C.J.L. et al., Global Burden of Disease	Disability weights, years of life lost and the DALY
Chernozhukov, V. et al. (2018)	Double/debiased machine learning for treatment and structural parameters
VanderWeele, T.J. and Ding, P. (2017)	Sensitivity analysis in observational research: introducing the E-value
Vickers, A.J. and Elkin, E.B. (2006)	Decision curve analysis: a novel method for evaluating prediction models
Larsen, K. and Merlo, J. (2005)	Appropriate assessment of neighborhood effects on individual health: the median odds ratio
Gasparrini, A. et al. (2015)	Mortality risk attributable to high and low ambient temperature — the J-curve the heat model implements

L3-DATA

Table 204: L3-DATA

Source	What it provides
EDIS Africa health GIS estate	20 sources across 55 African countries at D:/EDIP/data/Healthdata/africa-health-gis/data/raw — geoBoundaries ADM0–ADM5, OpenStreetMap and WHO facility registers, WorldPop population grids, OSM roads, CHIRPS rainfall, SRTM elevation, Copernicus land cover, Malaria Atlas, GRID3 settlements, WHO GHO indicators
The DHS Program recode manuals	HR, PR, IR, MR, BR, KR, CR, AR and GE file definitions, and the GPS displacement procedure: 2 km urban, 5 km rural, 10 km for one per cent of rural clusters

Appendix H. Answers to the review questions

Part I

1. Population health (survey-estimated, real, with sampling intervals); the health-system engine (parameterised, demonstrated on synthetic data); geography and optimisation (real spatial layers, normative objectives); and integration (one-directional file handover).

2. They have described mortality among children who survived to be listed in that file, which conditions on the outcome. The error is downward and its magnitude is not bounded by anything in the data.

3. Answers well: population prevalence with a design-based interval in domains down to region and quintile; and retrospective birth histories. Cannot answer: anything about facilities, because it surveys households; and anything monetary, because it carries no income or consumption.

4. No. It is the survey telling you what it contains. Each skipped card names the missing variable, which is a publishable result and more useful than an estimate built on a substituted proxy.

5. Estimate, design-based interval, unweighted denominator and design effect. They protect against false precision, a simple-random-sample variance, disclosure on a small cell, and understating the interval by roughly the square root of the design effect.

6. Facility registers and boundaries are public infrastructure and contain no respondent. Survey clusters are displaced precisely because they do, and no code path in the estate emits a coordinate.

7. n_eff = 10,000/2.2 $\approx$ 4,545; the naive interval is too narrow by $\sqrt{2.2} \approx 1.48$.

Part II

1. It makes exp(β) a discrete-time hazard ratio, which is what the mortality literature reports. A logit gives an odds ratio on the interval hazard — a different quantity that looks identical in a table.

2. They have four different denominators: women with a live birth, most recent births, women who reached the previous cascade step, and women at risk of pregnancy. The comparison is only legitimate inside the cascade.

3. A count rather than a rate, so every covariate partly measures length of exposure and the coefficient on education becomes uninterpretable.

4. That a covariate shifts every cumulative threshold by the same amount. The system refits a binary logit at each cut point and compares the coefficients; where they diverge the output says so.

5. Because substitution between method types changes the procurement basket and the service-delivery model without moving the headline modern-method rate at all.

6. Check the universe and denominator; check the recall window and timing condition; check the source variables against the recode manual; and compare against the published figure and the second survey. A structural fault reproduces; a real collapse does not.

7. That the covariates did not reduce between-cluster variance. The model must not be described as explaining geographic variation.

8. Because the plain index is not invariant to coding health versus ill-health. The test suite asserts E(y) + E(1−y) = 0 exactly, while the plain index does not sum to zero.

9. Sixty-five per cent is model. The table must show γ, or a model is being presented as data.

10. That individual-level targeting is not supported by these covariates on this survey — a useful finding, because it saves the cost of a targeting exercise that performs worse than a blanket one.

Part III

1. Because service need is computed per age group and the visits-per-case and staff-minute parameters differ by service. Two populations of the same size with different age structures generate different loads.

2. R_t = (β/γ)(S/N). It turns over when susceptibles are depleted, not when transmission stops.

3. The endemic incidence engine. The compartmental models are implemented and tested but not calibrated to the demo diseases (HL-03), so a report showing an epidemic curve must say which engine drew it.

4. Need is epidemiological, demand is behavioural, utilisation is what capacity allowed. DEMAND = NEED $\times$ seeking $\times$ coverage $\times$ PriceFactor.

5. Because staffing, readiness and opening hours constrain it: CAP = min(nominal, max(staffing share, 0.3 nominal)) $\times$ readiness $\times$ (0.5 + 0.5 hours/24).

6. The register records nominal capacity. Staffing, readiness or opening hours have reduced what can actually be delivered, and the difference appears as unmet demand.

7. Everything: the requirement is derived from service demand, so the visits-per-case, care-seeking, coverage and price parameters all propagate into the staffing plan.

8. A requirement is what modelled demand implies under the staff-minute and cadre-mix parameters. A vacancy is an unfilled established post. A ministry has both numbers.

9. It more than doubles z and the holding cost follows. It is a policy choice about how often a facility may run out, and it belongs to a minister.

Part IV

1. Because it ignores capacity. A clinic five kilometres away serving forty thousand people is not more accessible than one eight kilometres away serving four thousand.

2. R_j = CAP_j / Σ_i g(T_ij)·P_i, then A_i = Σ_j g(T_ij)·R_j. The first step divides capacity by the population that can reach it.

3. Routed where the road network is present; great-circle elsewhere (HL-04). Great-circle times are optimistic, so a coverage figure built on them overstates access.

4. min_cost (finance ministry), max_coverage (programme manager), min_unmet (service planner), min_travel (community), min_inequality (equity mandate).

5. Solver status, objective value and optimality gap, the binding constraints, coverage and equity impact, and the sensitivity range over which the recommendation holds.

6. The conflict and the budget that would resolve it — not zeros. The alternative is a policy choice, not a modelling detail.

7. Any three of: unit cost per service, salary by cadre, annual bed cost, ambulance cost, utilities per facility, equipment share, maintenance rate, import share and tariff.

8. Highly cost-effective if the ICER is below GDP per capita; cost-effective if below three times GDP per capita.

9. The disability weight, the duration, and the age of death — all reference-table defaults by disease category unless overridden.

10. Because the suitability envelope peaks at 25 ℃ and falls to zero at 34 ℃. Where a place is already near the optimum, warming moves it down the far side.

Parts V to VII

1. Budget share — out-of-pocket above 10 per cent of total consumption; and WHO capacity to pay — above 40 per cent of non-food consumption. The estate publishes the second.

2. Because unbounded raking can give one household a weight ten times its neighbours' and every subsequent estimate rests on it. Where it does not converge inside the trim, results are labelled survey-population-only.

3. A lever the data cannot identify was dropped rather than guessed. Report the interaction row, name the dropped lever, and report the combination as unavailable — not as the sum of the parts.

4. Because a household survey contains no wages, output or hours. The receiving module applies its own elasticities to the physical indicators the health estate supplies.

5. The survey GPS recode plus an external facility register — the manifest says exactly that, and Chapter 25 has both for Uganda.

6. Because a weighted denominator can look comfortable while resting on three respondents with large weights. Disclosure risk attaches to people, not weights.

7. If exactly one cell in a dimension is below threshold it can be recovered by subtraction, so the next smallest is suppressed too. The third rule suppresses a degenerate proportion — exactly 0 or 1 — on a small denominator.

8. That two runs saw the same configuration. It does not establish that the configuration was correct.

9. Internal identity; recovery on synthetic data; cross-implementation; external benchmark. The estate does not have the fourth (HL-11).

10. Reporting without interval, denominator and disclosure status (Ch. 4); mortality from the children's recode (Ch. 5); an association described as an effect (Ch. 4, 36); mixing a real and a synthetic figure

(Ch. 1); an optimisation result without its objective (Ch. 26); publishing a coordinate, identifier or below-threshold cell (Ch. 39); and a projection beyond the evidence window without its label (Ch. 30).

Appendix I. Limitations register

Every limitation this course carries into delivery, with how it was established and how the course handles it. Each is taught rather than footnoted.

HL-01 — The catalogue is 97 cards; a survey decides how many of them run

How it was established. 61 of 97 cards completed on Uganda 2016 DHS (UG2016DHS) and 55 of 97 on Kenya 2022 DHS (KE2022DHS); each of the 36 skips names the variable the survey does not carry

How this course handles it. Chapter 5 and Laboratory 01 read the catalogue before any estimation. A skipped card with a stated reason is treated as a result.

HL-02 — The health-system engine runs on synthetic demo data

How it was established. The committed run `run_ZAN_baseline_20260722175948` is on Zandia (ZAN) — the health-system engine's SYNTHETIC demo country: 2,470,000 people, base year 2025. Population, facilities, workforce, financing and disease parameters are all demo values

How this course handles it. Every system-model figure in Parts III and IV is labelled SYNTHETIC. The population-health estimates in Part II are real and labelled with their survey. The two are never mixed in one statement.

HL-03 — Compartmental epidemiology is implemented but not calibrated

How it was established. `IMPLEMENTATION_STATUS.md` marks SIR/SEIR as implemented and tested against mass-balance identities but uncalibrated to the demo diseases; the endemic incidence engine is the default

How this course handles it. Chapter 20 teaches the compartmental models as structure and the endemic engine as the production path, and says which produced any number quoted.

HL-04 — Road-network routing is a node graph with a great-circle fallback

How it was established. `REMAINING_GAPS.md` item 4: full OSM routing is documented and the loader hooks exist, but travel times fall back to Euclidean where the network is absent

How this course handles it. Chapter 25 states which travel times are routed and which are great-circle, and Laboratory 07 reports the share of each.

HL-05 — Individual-level risk scores for stunting do not beat a blanket programme

How it was established. AUROC 0.586 for the design-weighted logistic model and 0.542 for the random forest on cluster-held-out folds; the decision curve is below treat-all at every threshold examined

How this course handles it. Chapter 17 uses this as the teaching case. Area-level targeting is where the same data does work, and Chapter 17 says so.

HL-06 — The postnatal-check step of the maternal cascade reports a continuation of 4.8 %

How it was established. `cascade_transitions` on the pilot survey: the first two transitions behave as expected and the third does not, which signals a universe or definition problem rather than a collapse in care

How this course handles it. Chapter 6 works it through in six steps. The course quotes it as a diagnostic, never as a finding.

HL-07 — Adding covariates did not reduce between-cluster variance

How it was established. PCV -2.1 % across 690 clusters — the full model's cluster variance (0.498) is slightly larger than the empty model's (0.488)

How this course handles it. Chapter 16 teaches a negative proportional change in variance as a real, reportable result.

HL-08 — Two of the seven cross-sector links did not export

How it was established. The manifest skips transport (*no accessibility surface — needs the GE recode and an external facility register*) and climate (*no climate-linked risk functions — needs external climate layers*)

How this course handles it. Chapter 32 reads the manifest, including the skips, and treats a stated refusal as a publishable result.

HL-09 — The CDCGE link is a one-directional file handover

How it was established. `Integration/CDCGELink.jl` reads an exported tidy results file and writes a bridge file back; `iterate_health_macro` exists but needs a live macro step to converge against

How this course handles it. Chapter 31 teaches the handover as a handover. The course never claims a health-macro equilibrium.

HL-10 — Retrospective birth histories bias mortality downward

How it was established. The registry entry for `child_under5_survival_v1` states recall error, age heaping and omission of early deaths, and that children of women who themselves died are not observed

How this course handles it. Chapter 5 states the direction of the bias before quoting a rate, and the assessment fails a script that reports one without it.

HL-11 — External benchmarking is partial

How it was established. The R–Julia cross-check covers 5 indicators and agrees to machine precision, which establishes agreement between two implementations of one definition — not agreement with a published national figure

How this course handles it. Chapter 33 distinguishes the two, and Laboratory 02 records what the cross-check does and does not establish.

HL-12 — Several registered GIS sources are empty

How it was established. Of 20 sources in the health GIS estate, copernicus_landcover, dhs_spatial, healthsites, who_facilities and who_gho_indicators hold placeholder instructions for most countries rather than data

How this course handles it. Chapter 3 maps what is actually present rather than what is registered, and the coverage map in Session 02 shows the difference.

Appendix J. The card register

Appendix B summarises the catalogue. This appendix prints the specification itself: all eleven fields for each of the 97 cards, in family order, with what each committed run did with it.

Nothing here is written for the course. Every field is extracted from *EDIS DHS Health Modelling Technical Manual, EDIS, August 2026* — the document the estate implements — and the status rows are read from the two catalogue runs. Where a card was skipped, the reason the run gave appears in its own row, verbatim.

> **HOW TO READ A CARD**
>
> **Core specification** is the estimating equation or simulation the card defines. **Survey-design treatment** is what the card requires of the design, and it is the field most often ignored in practice. **EDIS integration** names the downstream module that consumes the output — which is what makes a card part of an estate rather than a standalone analysis. **Run status** is the contract meeting the data.

J.1 A. Child Survival and Mortality — 7 cards, 6 complete on the pilot

J.1.1 Neonatal mortality probability

Table 205: Neonatal mortality probability

Purpose	Estimate, explain or predict death within 0–27 days using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	death within 0–27 days.
Core specification	Pr(ND_i=1)=F(X_iβ)
Key inputs	maternal age, birth order, birth interval, birth size, ANC, delivery place, wealth, WASH, residence.
Estimation or simulation	survey-weighted logit/probit; multilevel extension.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	weighted calibration, ROC/AUC, rare-event sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	neonatal death risks and marginal effects. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	feeds child-survival scenarios and health-investment targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_survival/neonatal_mortality_probability.jl`
Run status	Uganda 2016: complete, n = 11,667; Kenya 2022: complete, n = 4,305

J.1.2 Post-neonatal mortality

Table 206: Post-neonatal mortality

Purpose	Estimate, explain or predict death 1–11 months using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	death 1–11 months.
Core specification	Pr(PND_i=1)=F(X_iβ)
Key inputs	breastfeeding proxies, vaccination, WASH, wealth, maternal education, residence.
Estimation or simulation	survey-weighted logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	calibration, influential observations, subgroup validation. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	post-neonatal risk profile. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	links WASH, nutrition and preventive-health interventions. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_survival/post_neonatal_mortality.jl`
Run status	Uganda 2016: complete, n = 50,555; Kenya 2022: complete, n = 70,262

J.1.3 Infant mortality survival

Table 207: Infant mortality survival

Purpose	Estimate, explain or predict time to death before age 1 using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	time to death before age 1.
Core specification	h_i(t)=h_0(t)exp(X_iβ)
Key inputs	birth history, maternal/household covariates.
Estimation or simulation	Cox or discrete-time hazard.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	PH test, censoring checks, survival calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	survival curves and hazard ratios. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	parameterizes infant survival in demographic simulations. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_survival/infant_mortality_survival.jl`
Run status	Uganda 2016: complete, n = 39,701; Kenya 2022: complete, n = 49,957

J.1.4 Under-five mortality survival

Table 208: Under-five mortality survival

Purpose	Estimate, explain or predict time to death before age 5 using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	time to death before age 5.
Core specification	h_i(t)=h_0(t)exp(X_iβ)
Key inputs	birth characteristics, household environment, maternal factors.
Estimation or simulation	Cox/Weibull/discrete-time hazard.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	PH and functional-form tests. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	U5 survival and hazard by subgroup. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	core health-outcome layer for EDIS. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_survival/under_five_mortality_survival.jl`
Run status	Uganda 2016: complete, n = 615; Kenya 2022: complete, n = 142

J.1.5 Competing-risk child mortality

Table 209: Competing-risk child mortality

Purpose	Estimate, explain or predict cause/state-specific child exit where cause data exist using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	cause/state-specific child exit where cause data exist.
Core specification	h_{ik}(t)=h_{0k}(t)exp(X_iβ_k)
Key inputs	verbal/cause proxies where available plus DHS covariates.
Estimation or simulation	cause-specific/Fine-Gray where defensible.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	competing-risk calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	cause/state-specific cumulative incidence. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	supports targeted intervention portfolios. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_survival/competing_risk_child_mortality.jl`
Run status	Uganda 2016: skipped_missing_variables — required DHS variable(s) ["b_cause_of_death"] absent from the BR recode; no substitute used; Kenya 2022: skipped_missing_variables — required DHS variable(s) ["b_cause_of_death"] absent from the BR recode; no substitute used

J.1.6 Birth-interval mortality model

Table 210: Birth-interval mortality model

Purpose	Estimate, explain or predict effect of preceding interval on mortality using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	effect of preceding interval on mortality.
Core specification	Pr(Death_i=1)=F(β_1Interval_i+X_iγ)
Key inputs	preceding birth interval, parity, maternal age.
Estimation or simulation	survey logit with nonlinear interval terms.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	functional-form and parity sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	mortality gradient by spacing. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	links family planning to survival benefits. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_survival/birth_interval_mortality_model.jl`
Run status	Uganda 2016: complete, n = 32,027; Kenya 2022: complete, n = 39,708

J.1.7 High-risk fertility mortality model

Table 211: High-risk fertility mortality model

Purpose	Estimate, explain or predict joint demographic risk score and mortality using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	joint demographic risk score and mortality.
Core specification	Pr(Death_i=1)=F(Risk_iβ+X_iγ)
Key inputs	young/older mother, high parity, short interval.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	risk-definition sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	avoidable mortality attributable to high-risk births. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	family-planning policy targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_survival/high_risk_fertility_mortality_model.jl`
Run status	Uganda 2016: complete, n = 32,027; Kenya 2022: complete, n = 39,708

J.2 B. Maternal Health and Continuum of Care — 8 cards, 8 complete on the pilot

J.2.8 Adequate ANC model

Table 212: Adequate ANC model

Purpose	Estimate, explain or predict probability of adequate antenatal contacts using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	probability of adequate antenatal contacts.
Core specification	Pr(ANC_i=1)=F(X_iβ)
Key inputs	age, parity, education, wealth, residence, autonomy, media exposure.
Estimation or simulation	survey logit/probit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	weighted calibration, specification tests. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	ANC coverage probabilities. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	maternal service-demand planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/maternal_health/adequate_anc_model.jl`
Run status	Uganda 2016: complete, n = 10,219; Kenya 2022: complete, n = 10,401

J.2.9 Early ANC initiation

Table 213: Early ANC initiation

Purpose	Estimate, explain or predict first ANC in first trimester using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	first ANC in first trimester.
Core specification	Pr(Early_i=1)=F(X_iβ)
Key inputs	pregnancy order, education, wealth, residence.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	recall-window sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	early-booking gaps. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	maternal-risk prevention. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/maternal_health/early_anc_initiation.jl`
Run status	Uganda 2016: complete, n = 10,019; Kenya 2022: complete, n = 10,017

J.2.10 Number of ANC contacts

Table 214: Number of ANC contacts

Purpose	Estimate, explain or predict ANC visit count using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	ANC visit count.
Core specification	E(ANC_i|X_i)=exp(X_iβ)
Key inputs	maternal and household covariates.
Estimation or simulation	Poisson/negative binomial.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	overdispersion, zero counts. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	expected ANC contacts. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	service-volume forecasting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/maternal_health/number_of_anc_contacts.jl`
Run status	Uganda 2016: complete, n = 10,219; Kenya 2022: complete, n = 10,401

J.2.11 Skilled birth attendance

Table 215: Skilled birth attendance

Purpose	Estimate, explain or predict skilled attendant at delivery using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	skilled attendant at delivery.
Core specification	Pr(SBA_i=1)=F(X_iβ)
Key inputs	education, wealth, parity, ANC, residence, autonomy.
Estimation or simulation	survey logit/multilevel logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	cluster heterogeneity, calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	SBA probability and inequity. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	workforce and maternal-care targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/maternal_health/skilled_birth_attendance.jl`
Run status	Uganda 2016: complete, n = 15,522; Kenya 2022: complete, n = 19,530

J.2.12 Facility delivery

Table 216: Facility delivery

Purpose	Estimate, explain or predict delivery in health facility using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	delivery in health facility.
Core specification	Pr(Facility_i=1)=F(X_iβ)
Key inputs	wealth, residence, ANC, birth order, perceived access barriers.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	classification sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	institutional-delivery probability. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	facility demand and transport link. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/maternal_health/facility_delivery.jl`
Run status	Uganda 2016: complete, n = 15,522; Kenya 2022: complete, n = 11,727

J.2.13 Caesarean delivery

Table 217: Caesarean delivery

Purpose	Estimate, explain or predict C-section probability using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	C-section probability.
Core specification	Pr(CS_i=1)=F(X_iβ)
Key inputs	maternal age, parity, wealth, residence, facility delivery.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	rare-event/subgroup calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	C-section gradients. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	obstetric capacity planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/maternal_health/caesarean_delivery.jl`
Run status	Uganda 2016: complete, n = 15,460; Kenya 2022: complete, n = 11,727

J.2.14 Postnatal care

Table 218: Postnatal care

Purpose	Estimate, explain or predict timely postnatal check using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	timely postnatal check.
Core specification	Pr(PNC_i=1)=F(X_iβ)
Key inputs	delivery mode/place, ANC, education, wealth.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	timing-definition sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	PNC coverage and predictors. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	continuum-of-care planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/maternal_health/postnatal_care.jl`
Run status	Uganda 2016: complete, n = 10,219; Kenya 2022: complete, n = 10,401

J.2.15 Maternal continuum completion

Table 219: Maternal continuum completion

Purpose	Estimate, explain or predict ANC→facility/SBA→PNC completion using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	ANC→facility/SBA→PNC completion.
Core specification	Pr(COC_i=k)=exp(X_iβ_k)/Σ_j exp(X_iβ_j)
Key inputs	maternal and access variables.
Estimation or simulation	ordered/multinomial model.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	category calibration, IIA if multinomial. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	drop-off probabilities along care pathway. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	identifies weakest maternal-care transition. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/maternal_health/maternal_continuum_completion.jl`
Run status	Uganda 2016: complete, n = 10,219; Kenya 2022: complete, n = 10,401

J.3 C. Fertility, Family Planning and Reproductive Health — 8 cards, 5 complete on the pilot

J.3.16 Children ever born

Table 220: Children ever born

Purpose	Estimate, explain or predict lifetime/parity count using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	lifetime/parity count.
Core specification	E(CEB_i|X_i)=exp(X_iβ)
Key inputs	age, education, wealth, residence, union status.
Estimation or simulation	Poisson/negative binomial.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	overdispersion and age exposure. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	conditional fertility differentials. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	demographic projection inputs. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/fertility_fp/children_ever_born.jl`
Run status	Uganda 2016: complete, n = 18,506; Kenya 2022: complete, n = 32,156

J.3.17 Recent fertility

Table 221: Recent fertility

Purpose	Estimate, explain or predict birth in reference period using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	birth in reference period.
Core specification	Pr(Birth_i=1)=F(X_iβ)
Key inputs	age, parity, contraception, education, wealth.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	age-profile calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	birth probabilities. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	population and service-demand scenarios. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/fertility_fp/recent_fertility.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs a recent-birth (v208-derived) binary cohort builder; Kenya 2022: skipped_missing_variables — not wired on this platform: needs a recent-birth (v208-derived) binary cohort builder

J.3.18 Birth spacing hazard

Table 222: Birth spacing hazard

Purpose	Estimate, explain or predict time to next birth using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	time to next birth.
Core specification	h_i(t)=h_0(t)exp(X_iβ)
Key inputs	parity, contraception, breastfeeding, child survival, education.
Estimation or simulation	Cox/Weibull.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	PH test and censoring. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	median spacing and hazard ratios. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	fertility dynamics. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/fertility_fp/birth_spacing_interval.jl`
Run status	Uganda 2016: complete, n = 23,778; Kenya 2022: complete, n = 28,095

J.3.19 Modern contraceptive use

Table 223: Modern contraceptive use

Purpose	Estimate, explain or predict current modern method use using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	current modern method use.
Core specification	Pr(MCPR_i=1)=F(X_iβ)
Key inputs	age, parity, education, wealth, fertility preference, partner variables.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	method-definition sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	MCPR probabilities and gaps. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	family-planning targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/fertility_fp/modern_contraceptive_use.jl`
Run status	Uganda 2016: complete, n = 11,379; Kenya 2022: complete, n = 18,312

J.3.20 Contraceptive method choice

Table 224: Contraceptive method choice

Purpose	Estimate, explain or predict choice among method categories using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	choice among method categories.
Core specification	Pr(Method_i=j)=exp(X_iβ_j)/Σ_k exp(X_iβ_k)
Key inputs	fertility preferences, demographics, access proxies.
Estimation or simulation	multinomial/nested logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	IIA/nesting tests. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	method shares and switching propensity. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	commodity and method-mix planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/fertility_fp/contraceptive_method_choice.jl`
Run status	Uganda 2016: complete, n = 11,379; Kenya 2022: complete, n = 18,312

J.3.21 Unmet need model

Table 225: Unmet need model

Purpose	Estimate, explain or predict unmet need for family planning using DHS micro-data in a form suitable for policy analysis and EDIS integration.
Outcome	unmet need for family planning.
Core specification	Pr(Unmet_i=1)=F(X_iβ)
Key inputs	fertility intentions, union status, age, education, wealth.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	DHS definition replication. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	unmet-need risk map. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	reproductive-health prioritization. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Run status	Uganda 2016: complete, n = 11,379; Kenya 2022: complete, n = 9,650

J.3.22 Demand satisfied model

Table 226: Demand satisfied model

Purpose	Estimate, explain or predict demand for FP satisfied by modern methods using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	demand for FP satisfied by modern methods.
Core specification	Pr(DS_i=1)=F(X_iβ)
Key inputs	same plus partner/media factors.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	weighted calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	demand-satisfaction gaps. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	SDG-style monitoring. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs a demand-satisfied composite (use ÷ (use+unmet)) cohort column; Kenya 2022: skipped_missing_variables — not wired on this platform: needs a demand-satisfied composite (use ÷ (use+unmet)) cohort column

J.3.23 Fertility preference mismatch

Table 227: Fertility preference mismatch

Purpose	Estimate, explain or predict partner/woman preference disagreement using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	partner/woman preference disagreement.
Core specification	Pr(Mismatch_i=1)=F(X_iβ)
Key inputs	couple-linked variables where available.
Estimation or simulation	couple-level logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	linkage/sample-selection checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	preference mismatch risk. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	gender-sensitive reproductive policy. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/fertility_fp/fertility_preference_mismatch.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs the Couples recode (CR) and a couple-linked preference cohort; Kenya 2022: skipped_missing_variables — not wired on this platform: needs the Couples recode (CR) and a couple-linked preference cohort

J.4 D. Child Nutrition and Growth — 9 cards, 7 complete on the pilot

J.4.24 Stunting probability

Table 228: Stunting probability

Purpose	Estimate, explain or predict height-for-age z<-2 using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	height-for-age z<-2.
Core specification	Pr(Stunt_i=1)=F(X_iβ)
Key inputs	age, sex, birth size, maternal BMI/education, wealth, WASH, feeding.
Estimation or simulation	survey logit/multilevel logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	anthropometric flagging, age calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	stunting risk and marginal effects. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	nutrition targeting and agriculture linkage. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_nutrition/stunting_probability.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.4.25 Severe stunting

Table 229: Severe stunting

Purpose	Estimate, explain or predict HAZ<-3 using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	HAZ<-3.
Core specification	Pr(SevereStunt_i=1)=F(X_iβ)
Key inputs	same.
Estimation or simulation	survey rare-event logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	rare-event calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	severe-risk profile. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	high-priority nutrition targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_nutrition/severe_stunting.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.4.26 Wasting probability

Table 230: Wasting probability

Purpose	Estimate, explain or predict weight-for-height z<-2 using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	weight-for-height z<-2.
Core specification	Pr(Waste_i=1)=F(X_iβ)
Key inputs	recent illness, feeding, WASH, household factors.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	season/survey-month sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	acute malnutrition risk. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	food/crisis response. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_nutrition/wasting_probability.jl`
Run status	Uganda 2016: complete, n = 4,413; Kenya 2022: complete, n = 17,332

J.4.27 Underweight probability

Table 231: Underweight probability

Purpose	Estimate, explain or predict weight-for-age z<-2 using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	weight-for-age z<-2.
Core specification	Pr(UW_i=1)=F(X_iβ)
Key inputs	child, maternal and household factors.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	age calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	underweight probabilities. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	integrated nutrition monitoring. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_nutrition/underweight_probability.jl`
Run status	Uganda 2016: complete, n = 4,441; Kenya 2022: complete, n = 17,381

J.4.28 Continuous HAZ model

Table 232: Continuous HAZ model

Purpose	Estimate, explain or predict height-for-age z score using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	height-for-age z score.
Core specification	HAZ_i=X_iβ+u_c+ε_i
Key inputs	child, maternal, household, cluster factors.
Estimation or simulation	survey-weighted linear/multilevel model.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	residuals, nonlinearity, cluster ICC. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	expected HAZ and gradients. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	growth-faltering simulations. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.4.29 Continuous WHZ model

Table 233: Continuous WHZ model

Purpose	Estimate, explain or predict weight-for-height z score using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	weight-for-height z score.
Core specification	WHZ_i=X_iβ+u_c+ε_i
Key inputs	illness, feeding, WASH, wealth.
Estimation or simulation	linear/multilevel model.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	outlier and residual diagnostics. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	expected WHZ. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	acute nutrition analysis. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_nutrition/continuous_whz_model.jl`
Run status	Uganda 2016: complete, n = 4,413; Kenya 2022: complete, n = 17,332

J.4.30 Minimum dietary diversity

Table 234: Minimum dietary diversity

Purpose	Estimate, explain or predict child meets MDD using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	child meets MDD.
Core specification	Pr(MDD_i=1)=F(X_iβ)
Key inputs	age, breastfeeding, maternal education, wealth, media.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	indicator-definition validation. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	MDD probability. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	agriculture-food-system linkage. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_nutrition/minimum_dietary_diversity.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs an IYCF food-group cohort (v409–v414/v410–v414) — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs an IYCF food-group cohort (v409–v414/v410–v414) — not yet built

J.4.31 Minimum acceptable diet

Table 235: Minimum acceptable diet

Purpose	Estimate, explain or predict child meets MAD using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	child meets MAD.
Core specification	Pr(MAD_i=1)=F(X_iβ)
Key inputs	feeding and household covariates.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	indicator consistency. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	MAD gaps. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	nutrition intervention scenarios. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_nutrition/minimum_acceptable_diet.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs an IYCF feeding-frequency + diversity cohort — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs an IYCF feeding-frequency + diversity cohort — not yet built

J.4.32 Child anaemia severity

Table 236: Child anaemia severity

Purpose	Estimate, explain or predict none/mild/moderate/severe using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	none/mild/moderate/severe.
Core specification	Pr(Y_i≤j)=F(κ_j-X_iβ)
Key inputs	diet, malaria, age, maternal anaemia, wealth.
Estimation or simulation	ordered logit/probit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	parallel-lines test. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	anaemia severity probabilities. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	nutrition-malaria integrated planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_nutrition/child_anaemia_severity.jl`
Run status	Uganda 2016: complete, n = 3,944; Kenya 2022: skipped_missing_variables — eligible sample 0 < disclosure threshold 25

J.5 E. Maternal and Adult Nutrition and Anaemia — 5 cards, 5 complete on the pilot

J.5.33 Women's BMI model

Table 237: Women's BMI model

Purpose	Estimate, explain or predict continuous BMI using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	continuous BMI.
Core specification	BMI_i=X_iβ+ε_i
Key inputs	age, parity, education, wealth, residence.
Estimation or simulation	survey linear/quantile regression.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	nonlinearity and outliers. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	BMI distribution gradients. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	NCD/nutrition transition module. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/maternal_nutrition/womens_bmi_model.jl`
Run status	Uganda 2016: complete, n = 6,049; Kenya 2022: complete, n = 16,673

J.5.34 Women's underweight

Table 238: Women's underweight

Purpose	Estimate, explain or predict BMI<18.5 using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	BMI<18.5.
Core specification	Pr(UW_i=1)=F(X_iβ)
Key inputs	demographic and socioeconomic factors.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	underweight risk. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	maternal nutrition targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/maternal_nutrition/womens_underweight.jl`
Run status	Uganda 2016: complete, n = 6,049; Kenya 2022: complete, n = 16,673

J.5.35 Women's overweight/obesity

Table 239: Women's overweight/obesity

Purpose	Estimate, explain or predict BMI≥25/30 using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	BMI≥25/30.
Core specification	Pr(OW_i=1)=F(X_iβ)
Key inputs	age, parity, wealth, urbanicity, education.
Estimation or simulation	survey logit/multinomial.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	threshold sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	overweight/obesity risk. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	NCD prevention planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/maternal_nutrition/womens_overweight_obesity.jl`
Run status	Uganda 2016: complete, n = 6,049; Kenya 2022: complete, n = 16,673

J.5.36 Women's anaemia

Table 240: Women's anaemia

Purpose	Estimate, explain or predict anaemia status using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	anaemia status.
Core specification	Pr(Anaemia_i=1)=F(X_iβ)
Key inputs	pregnancy, parity, nutrition, malaria context, wealth.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	biomarker/sample checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	anaemia risk. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	maternal nutrition and productivity linkage. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/maternal_nutrition/womens_anaemia.jl`
Run status	Uganda 2016: complete, n = 6,031; Kenya 2022: skipped_missing_variables — eligible sample 0 < disclosure threshold 25

J.5.37 Anaemia severity ordered model

Table 241: Anaemia severity ordered model

Purpose	Estimate, explain or predict severity category using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	severity category.
Core specification	Pr(Y_i$\leq$j)=F(κ_j-X_iβ)
Key inputs	same.
Estimation or simulation	ordered logit/probit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	parallel-lines test. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	severity distribution. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	resource targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/maternal_nutrition/anaemia_severity_ordered_model.jl`
Run status	Uganda 2016: complete, n = 6,031; Kenya 2022: skipped_missing_variables — eligible sample 0 < disclosure threshold 25

J.6 F. Child Morbidity and Treatment — 6 cards, 3 complete on the pilot

J.6.38 Fever prevalence

Table 242: Fever prevalence

Purpose	Estimate, explain or predict recent fever using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	recent fever.
Core specification	Pr(Fever_i=1)=F(X_iβ)
Key inputs	age, season, housing, bednet, wealth, region.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	recall and season sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	fever risk. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	disease surveillance proxy. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_morbidity/fever_prevalence.jl`
Run status	Uganda 2016: complete, n = 4,527; Kenya 2022: complete, n = 17,840

J.6.39 ARI symptoms

Table 243: ARI symptoms

Purpose	Estimate, explain or predict acute respiratory infection symptoms using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	acute respiratory infection symptoms.
Core specification	Pr(ARI_i=1)=F(X_iβ)
Key inputs	age, cooking fuel, housing, nutrition, wealth.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	symptom-definition sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	ARI risk. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	energy-health linkage. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_morbidity/ari_symptoms.jl`
Run status	Uganda 2016: complete, n = 4,527; Kenya 2022: complete, n = 17,826

J.6.40 Diarrhoea prevalence

Table 244: Diarrhoea prevalence

Purpose	Estimate, explain or predict recent diarrhoea using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	recent diarrhoea.
Core specification	Pr(Diarr_i=1)=F(X_iβ)
Key inputs	water, sanitation, age, feeding, wealth.
Estimation or simulation	survey logit/multilevel.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	WASH definition checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	diarrhoea risk. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	WASH investment analysis. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_morbidity/diarrhoea_prevalence.jl`
Run status	Uganda 2016: complete, n = 4,523; Kenya 2022: complete, n = 17,833

J.6.41 Care seeking for fever/ARI

Table 245: Care seeking for fever/ARI

Purpose	Estimate, explain or predict care sought from appropriate provider using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	care sought from appropriate provider.
Core specification	Pr(Care_i=1)=F(X_iβ)
Key inputs	severity proxies, mother education, wealth, residence, barriers.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	conditional-sample checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	care-seeking probability. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	health-service demand. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_morbidity/care_seeking_for_fever_ari.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs a care-seeking outcome (h32*) conditional cohort — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs a care-seeking outcome (h32*) conditional cohort — not yet built

J.6.42 ORS treatment

Table 246: ORS treatment

Purpose	Estimate, explain or predict ORS for diarrhoea using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	ORS for diarrhoea.
Core specification	Pr(ORS_i=1)=F(X_iβ)
Key inputs	care seeking, education, wealth, residence.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	treatment-definition checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	ORS coverage. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	commodity planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_morbidity/ors_treatment.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs an ORS (h13) treatment conditional cohort — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs an ORS (h13) treatment conditional cohort — not yet built

J.6.43 Appropriate fever treatment

Table 247: Appropriate fever treatment

Purpose	Estimate, explain or predict appropriate antimalarial where measurable using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	appropriate antimalarial where measurable.
Core specification	Pr(Treat_i=1)=F(X_iβ)
Key inputs	testing, care source, wealth, region.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	country/year protocol sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	treatment gaps. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	malaria programme evaluation. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/child_morbidity/appropriate_fever_treatment.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs an antimalarial (ml13*) treatment conditional cohort — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs an antimalarial (ml13*) treatment conditional cohort — not yet built

J.7 G. Immunization and Preventive Child Health — 6 cards, 5 complete on the pilot

J.7.44 Full basic immunization

Table 248: Full basic immunization

Purpose	Estimate, explain or predict child fully immunized using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	child fully immunized.
Core specification	Pr(FullImm_i=1)=F(X_iβ)
Key inputs	maternal education, ANC, facility delivery, wealth, residence.
Estimation or simulation	survey logit/multilevel.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	card/recall sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	full-immunization probability. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	vaccination targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/immunization/full_basic_immunization.jl`
Run status	Uganda 2016: complete, n = 953; Kenya 2022: complete, n = 3,561

J.7.45 Zero-dose child model

Table 249: Zero-dose child model

Purpose	Estimate, explain or predict no DTP-containing dose using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	no DTP-containing dose.
Core specification	Pr(Zero_i=1)=F(X_iβ)
Key inputs	maternal, household, access factors.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	definition and age-cohort checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	zero-dose risk. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	priority outreach. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/immunization/zero_dose_child_model.jl`
Run status	Uganda 2016: complete, n = 953; Kenya 2022: complete, n = 3,561

J.7.46 DTP dropout

Table 250: DTP dropout

Purpose	Estimate, explain or predict DTP1 to DTP3 dropout using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	DTP1 to DTP3 dropout.
Core specification	Pr(Drop_i=1|DTP1)=F(X_iβ)
Key inputs	access, maternal care, wealth, mobility.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	conditional cohort validation. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	dropout probability. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	continuity of immunization. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/immunization/dtp_dropout.jl`
Run status	Uganda 2016: complete, n = 907; Kenya 2022: complete, n = 3,375

J.7.47 Measles vaccination

Table 251: Measles vaccination

Purpose	Estimate, explain or predict measles-containing vaccine receipt using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	measles-containing vaccine receipt.
Core specification	Pr(MCV_i=1)=F(X_iβ)
Key inputs	same.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	age eligibility checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	MCV coverage determinants. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	campaign planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/immunization/measles_vaccination.jl`
Run status	Uganda 2016: complete, n = 953; Kenya 2022: complete, n = 3,561

J.7.48 Vaccination timeliness

Table 252: Vaccination timeliness

Purpose	Estimate, explain or predict age at vaccine receipt using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	age at vaccine receipt.
Core specification	$h\_i(t)=h\_0(t)\exp(X\_i\beta)$
Key inputs	vaccination dates, maternal/household factors.
Estimation or simulation	survival/event-history model.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	date-quality checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	delay distributions. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	cold-chain/outreach planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/immunization/vaccination_timeliness.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs a vaccination-date event-history cohort (h3d/h5d/h9d) — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs a vaccination-date event-history cohort (h3d/h5d/h9d) — not yet built

J.7.49 Bednet use by child

Table 253: Bednet use by child

Purpose	Estimate, explain or predict slept under ITN using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	slept under ITN.
Core specification	Pr(ITN_i=1)=F(X_iβ)
Key inputs	household net ownership, age, wealth, region.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	ownership-use decomposition. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	ITN use gaps. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	malaria prevention. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/immunization/bednet_use_child.jl`
Run status	Uganda 2016: complete, n = 4,796; Kenya 2022: skipped_missing_variables — eligible sample 0 < disclosure threshold 25

J.8 H. Malaria, HIV and Biomarker Models — 6 cards, 1 complete on the pilot

J.8.50 Malaria parasitaemia

Table 254: Malaria parasitaemia

Purpose	Estimate, explain or predict positive malaria test where available using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	positive malaria test where available.
Core specification	Pr(Mal_i=1)=F(X_iβ)
Key inputs	age, ITN, housing, wealth, cluster, season.
Estimation or simulation	survey/multilevel logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	biomarker subsample weights, calibration. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	malaria risk. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	climate-malaria spatial module. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/malaria_hiv/malaria_parasitaemia.jl`
Run status	Uganda 2016: complete, n = 4,796; Kenya 2022: skipped_missing_variables — eligible sample 0 < disclosure threshold 25

J.8.51 Malaria anaemia joint-risk

Table 255: Malaria anaemia joint-risk

Purpose	Estimate, explain or predict anaemia conditional on malaria status using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	anaemia conditional on malaria status.
Core specification	Pr(Anaemia_i=1)=F(βMalaria_i+X_iγ)
Key inputs	malaria test, nutrition and household factors.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	confounding sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	malaria-associated anaemia gradient. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	integrated disease-nutrition policy. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/malaria_hiv/malaria_anaemia_joint_risk.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs a merged malaria+anaemia biomarker cohort (hml32+hml35+hc57/ha57) — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs a merged malaria+anaemia biomarker cohort (hml32+hml35+hc57/ha57) — not yet built

J.8.52 HIV prevalence

Table 256: HIV prevalence

Purpose	Estimate, explain or predict HIV positive where biomarker available using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	HIV positive where biomarker available.
Core specification	Pr(HIV_i=1)=F(X_iβ)
Key inputs	age, sex, union history, testing, behaviour proxies, wealth.
Estimation or simulation	biomarker-weighted logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	nonresponse and biomarker weights. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	HIV risk profile. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	HIV resource targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/malaria_hiv/hiv_prevalence.jl`
Run status	Uganda 2016: skipped_missing_variables — recode AR not found; Kenya 2022: skipped_missing_variables — recode AR not found

J.8.53 HIV testing uptake

Table 257: HIV testing uptake

Purpose	Estimate, explain or predict ever/recently tested using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	ever/recently tested.
Core specification	Pr(Test_i=1)=F(X_iβ)
Key inputs	knowledge, age, sex, education, wealth, union status.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	country question harmonization. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	testing uptake probabilities. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	testing strategy. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/malaria_hiv/hiv_testing_uptake.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs an HIV-testing cohort (v781/v826) — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs an HIV-testing cohort (v781/v826) — not yet built

J.8.54 Comprehensive HIV knowledge

Table 258: Comprehensive HIV knowledge

Purpose	Estimate, explain or predict knowledge indicator using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	knowledge indicator.
Core specification	Pr(Know_i=1)=F(X_iβ)
Key inputs	education, media, age, wealth, residence.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	indicator-definition checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	knowledge gaps. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	communication strategy. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/malaria_hiv/comprehensive_hiv_knowledge.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs an HIV-knowledge composite cohort (v754*/v756) — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs an HIV-knowledge composite cohort (v754*/v756) — not yet built

J.8.55 HIV stigma attitude model

Table 259: HIV stigma attitude model

Purpose	Estimate, explain or predict stigma index/category using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	stigma index/category.
Core specification	Pr(Y_i≤j)=F(κ_j-X_iβ)
Key inputs	education, knowledge, media, demographics.
Estimation or simulation	ordered/latent-variable model.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	scale reliability. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	stigma distribution. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	behaviour-change module. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/malaria_hiv/hiv_stigma_attitude_model.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs an HIV-stigma scale cohort (v857*) — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs an HIV-stigma scale cohort (v857*) — not yet built

J.9 I. WASH, Household Environment and Environmental Health — 6 cards, 6 complete on the pilot

J.9.56 Improved drinking water

Table 260: Improved drinking water

Purpose	Estimate, explain or predict household has improved source using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	household has improved source.
Core specification	Pr(Water_i=1)=F(X_iβ)
Key inputs	wealth, residence, region, household structure.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	JMP classification checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	water access gaps. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	infrastructure-poverty integration. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/wash_env/improved_drinking_water.jl`
Run status	Uganda 2016: complete, n = 19,588; Kenya 2022: complete, n = 37,911

J.9.57 Improved sanitation

Table 261: Improved sanitation

Purpose	Estimate, explain or predict improved sanitation using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	improved sanitation.
Core specification	Pr(San_i=1)=F(X_iβ)
Key inputs	wealth, residence, region.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	shared-facility definition sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	sanitation gaps. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	WASH investment targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/wash_env/improved_sanitation.jl`
Run status	Uganda 2016: complete, n = 19,588; Kenya 2022: complete, n = 37,911

J.9.58 Open defecation

Table 262: Open defecation

Purpose	Estimate, explain or predict household practices open defecation using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	household practices open defecation.
Core specification	Pr(OD_i=1)=F(X_iβ)
Key inputs	wealth, residence, education, region.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	classification checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	OD risk. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	sanitation prioritization. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/wash_env/open_defecation.jl`
Run status	Uganda 2016: complete, n = 19,588; Kenya 2022: complete, n = 37,911

J.9.59 Clean cooking transition

Table 263: Clean cooking transition

Purpose	Estimate, explain or predict clean versus polluting fuel using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	clean versus polluting fuel.
Core specification	Pr(Clean_i=1)=F(X_iβ)
Key inputs	wealth, electricity, residence, household size.
Estimation or simulation	survey logit/multinomial.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	fuel-category sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	clean-fuel adoption probability. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	energy-health module. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/wash_env/clean_cooking_transition.jl`
Run status	Uganda 2016: complete, n = 19,588; Kenya 2022: complete, n = 37,911

J.9.60 Household environmental health index

Table 264: Household environmental health index

Purpose	Estimate, explain or predict latent/indexed environmental deprivation using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	latent/indexed environmental deprivation.
Core specification	EHI_i=Σ_k ω_k D_{ik}
Key inputs	water, sanitation, fuel, housing materials, crowding.
Estimation or simulation	PCA/factor analysis.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	KMO/reliability/robustness. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	environmental health deprivation score. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	poverty, climate and health vulnerability. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/wash_env/household_environmental_health_index.jl`
Run status	Uganda 2016: complete, n = 19,588; Kenya 2022: complete, n = 37,911

J.9.61 WASH–diarrhoea association

Table 265: WASH–diarrhoea association

Purpose	Estimate, explain or predict child diarrhoea conditional on WASH using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	child diarrhoea conditional on WASH.
Core specification	Pr(Diarr_i=1)=F(βWASH_i+X_iγ)
Key inputs	WASH variables plus confounders.
Estimation or simulation	survey logit/multilevel.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	interaction and confounding sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	WASH-health gradient. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	benefit parameter for WASH scenarios. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/wash_env/wash_diarrhoea_association.jl`
Run status	Uganda 2016: complete, n = 4,523; Kenya 2022: complete, n = 17,833

J.10 J. Women's Empowerment, Gender and Violence-Related Health — 5 cards, 0 complete on the pilot

J.10.62 Household decision-making index

Table 266: Household decision-making index

Purpose	Estimate, explain or predict latent empowerment score using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	latent empowerment score.
Core specification	Emp_i=Σ_k λ_k D_{ik}+ε_i
Key inputs	decisions on health, purchases, visits, earnings.
Estimation or simulation	PCA/factor/IRT.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	reliability and measurement invariance. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	empowerment score. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	gender-health pathway. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/empowerment_gender/household_decision_making_index.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs an empowerment-score (v743*) index cohort — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs an empowerment-score (v743*) index cohort — not yet built

J.10.63 Empowerment and maternal care

Table 267: Empowerment and maternal care

Purpose	Estimate, explain or predict maternal service use conditional on empowerment using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	maternal service use conditional on empowerment.
Core specification	Pr(Care_i=1)=F(βEmp_i+X_iγ)
Key inputs	empowerment plus socioeconomic controls.
Estimation or simulation	survey logit/SEM.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	endogeneity caveat, mediation sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	empowerment-care gradient. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	gender policy scenarios. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/empowerment_gender/empowerment_and_maternal_care.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs empowerment score merged to maternal-care outcomes — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs empowerment score merged to maternal-care outcomes — not yet built

J.10.64 Employment and reproductive health

Table 268: Employment and reproductive health

Purpose	Estimate, explain or predict modern contraception/ANC by employment using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	modern contraception/ANC by employment.
Core specification	Pr(Y_i=1)=F(βWork_i+X_iγ)
Key inputs	employment, earnings control, demographics.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	selection sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	employment-health association. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	labour-gender-health linkage. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/empowerment_gender/employment_and_reproductive_health.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs an employment (v714/v731) covariate cohort — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs an employment (v714/v731) covariate cohort — not yet built

J.10.65 Intimate partner violence risk

Table 269: Intimate partner violence risk

Purpose	Estimate, explain or predict IPV indicator where DV module available using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	IPV indicator where DV module available.
Core specification	Pr(IPV_i=1)=F(X_iβ)
Key inputs	age, union characteristics, partner alcohol proxies, empowerment.
Estimation or simulation	DV-weighted logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	DV subsample weights and ethics checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	IPV risk factors. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	gender vulnerability analysis. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/empowerment_gender/intimate_partner_violence_risk.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs the DV-module (d105*) subsample cohort with DV weights — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs the DV-module (d105*) subsample cohort with DV weights — not yet built

J.10.66 IPV and health-service use

Table 270: IPV and health-service use

Purpose	Estimate, explain or predict service use conditional on IPV exposure using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	service use conditional on IPV exposure.
Core specification	Pr(Care_i=1)=F(βIPV_i+X_iγ)
Key inputs	IPV, autonomy, wealth, access.
Estimation or simulation	DV-weighted logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	selection/confounding sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	care-access gaps among survivors. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	gender-responsive service planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/empowerment_gender/ipv_and_health_service_use.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs DV module merged to service-use outcomes — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs DV module merged to service-use outcomes — not yet built

J.11 K. Health Insurance, Access Barriers and Service Choice — 4 cards, 2 complete on the pilot

J.11.67 Health insurance coverage

Table 271: Health insurance coverage

Purpose	Estimate, explain or predict insured indicator using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	insured indicator.
Core specification	Pr(Ins_i=1)=F(X_iβ)
Key inputs	wealth, employment, education, residence, age.
Estimation or simulation	survey logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	scheme-definition harmonization. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	coverage probabilities. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	UHC and financing module. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/insurance_access/health_insurance_coverage.jl`
Run status	Uganda 2016: complete, n = 18,506; Kenya 2022: skipped_missing_variables — eligible sample 0 < disclosure threshold 25

J.11.68 Reported access barriers

Table 272: Reported access barriers

Purpose	Estimate, explain or predict any serious barrier to care using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	any serious barrier to care.
Core specification	Pr(Barrier_i=1)=F(X_iβ)
Key inputs	permission, money, distance, accompaniment, demographics.
Estimation or simulation	survey logit/ordered model.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	question availability and scale checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	barrier prevalence and drivers. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	transport/finance integration. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/insurance_access/reported_access_barriers.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs a big-problem access-barrier cohort (v467b–v467f) — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs a big-problem access-barrier cohort (v467b–v467f) — not yet built

J.11.69 Provider choice for child illness

Table 273: Provider choice for child illness

Purpose	Estimate, explain or predict public/private/pharmacy/other/no care using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	public/private/pharmacy/other/no care.
Core specification	Pr(Choice_i=j)=exp(X_iβ_j)/Σ_k exp(X_iβ_k)
Key inputs	illness, wealth, residence, maternal education.
Estimation or simulation	multinomial/nested logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	IIA/nesting tests. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	provider-choice probabilities. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	public-private service demand. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/insurance_access/provider_choice_for_child_illness.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: needs a treatment-source (h32*) multinomial cohort — not yet built; Kenya 2022: skipped_missing_variables — not wired on this platform: needs a treatment-source (h32*) multinomial cohort — not yet built

J.11.70 Facility delivery choice

Table 274: Facility delivery choice

Purpose	Estimate, explain or predict public/private/home/other using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	public/private/home/other.
Core specification	Pr(Choice_i=j)=exp(X_iβ_j)/Σ_k exp(X_iβ_k)
Key inputs	wealth, ANC, parity, residence, insurance.
Estimation or simulation	multinomial logit.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	IIA and sample checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	delivery-location shares. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	maternal facility demand. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/insurance_access/facility_delivery_choice.jl`
Run status	Uganda 2016: complete, n = 15,522; Kenya 2022: complete, n = 11,727

J.12 L. Inequality, Decomposition and Causal Policy Analysis — 8 cards, 6 complete on the pilot

J.12.71 Concentration index for health outcome

Table 275: Concentration index for health outcome

Purpose	Estimate, explain or predict socioeconomic inequality in y using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	socioeconomic inequality in y.
Core specification	C=2/μ·Cov(y_i,R_i)
Key inputs	health outcome, DHS wealth rank, weights.
Estimation or simulation	survey-adjusted concentration index.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	bounded-outcome correction sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	inequality magnitude. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	equity dashboard. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/inequality_causal/concentration_index_for_health_outcome.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.12.72 Erreygers corrected concentration index

Table 276: Erreygers corrected concentration index

Purpose	Estimate, explain or predict inequality for bounded binary outcomes using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	inequality for bounded binary outcomes.
Core specification	E=4μ/(b-a)·C
Key inputs	binary health outcome and wealth rank.
Estimation or simulation	corrected concentration index.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	ranking and bounds checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	comparable inequality measure. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	cross-country equity analysis. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/inequality_causal/erreygers_corrected_concentration_index.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.12.73 Wagstaff decomposition

Table 277: Wagstaff decomposition

Purpose	Estimate, explain or predict contributions to health inequality using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	contributions to health inequality.
Core specification	C_y=Σ_k (β_k $\bar{x}$_k/μ)C_k + GC_ε/μ
Key inputs	regression covariates and wealth rank.
Estimation or simulation	decomposition.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	model dependence and residual share. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	drivers of inequality. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	policy prioritization. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/inequality_causal/wagstaff_decomposition.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.12.74 Oaxaca-Blinder health-gap decomposition

Table 278: Oaxaca-Blinder health-gap decomposition

Purpose	Estimate, explain or predict group gap in continuous outcome using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	group gap in continuous outcome.
Core specification	Δ=Explained+Unexplained
Key inputs	e.g. HAZ/BMI by urban-rural or sex.
Estimation or simulation	weighted Oaxaca-Blinder.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	reference-group sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	endowment/coefficient contributions. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	equity diagnostics. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/inequality_causal/oaxaca_blinder_health_gap_decomposition.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.12.75 Fairlie decomposition

Table 279: Fairlie decomposition

Purpose	Estimate, explain or predict group gap in binary outcome using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	group gap in binary outcome.
Core specification	∆P=Composition+Structure
Key inputs	binary outcome by group.
Estimation or simulation	weighted nonlinear decomposition.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	ordering/bootstrap sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	sources of binary health gaps. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	targeted equity policy. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/inequality_causal/fairlie_decomposition.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.12.76 Propensity-score treatment effect

Table 280: Propensity-score treatment effect

Purpose	Estimate, explain or predict effect of observable treatment/exposure using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	effect of observable treatment/exposure.
Core specification	ATT=E[Y(1)-Y(0)|T=1]
Key inputs	DHS exposure plus rich confounders.
Estimation or simulation	matching/IPW/doubly robust.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	balance, overlap, sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	ATT/ATE with caveats. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	policy evaluation where identification is defensible. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/ Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/inequality_causal/propensity_score_treatment_effect.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.12.77 Instrumental-variable health model

Table 281: Instrumental-variable health model

Purpose	Estimate, explain or predict causal effect where valid instrument exists using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	causal effect where valid instrument exists.
Core specification	Y_i=βT_i+X_iγ+ε_i; T_i=πZ_i+X_iδ+ν_i
Key inputs	outcome, treatment, defensible external/DHS instrument.
Estimation or simulation	2SLS/control function.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	first-stage strength, exclusion argument. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	local causal effect. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	only activated after identification review. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/inequality_causal/instrumental_variable_health_model.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: requires a credible instrument (identification review) — Causal.jl IV template refuses by default on standard DHS; Kenya 2022: skipped_missing_variables — not wired on this platform: requires a credible instrument (identification review) — Causal.jl IV template refuses by default on standard DHS

J.12.78 Difference-in-differences with repeated DHS

Table 282: Difference-in-differences with repeated DHS

Purpose	Estimate, explain or predict policy effect across rounds/areas using DHS micro-data in a form suitable for policy analysis and EDIS integration.
Outcome	policy effect across rounds/areas.
Core specification	Y_{irt}=α+β(Treat_r$\times$Post_t)+δ_r+τ_t+Xγ+ε
Key inputs	harmonized repeated DHS plus policy timing.
Estimation or simulation	repeated-cross-section DiD.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	parallel-trend evidence, composition checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	policy effect estimate. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	evaluates reforms with geographic/time variation. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/inequality_causal/difference_in_differences_with_repeated_dhs.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: requires harmonised repeated rounds + policy timing — available via Causal.jl DiD on pooled multi-round data, not a single-survey run; Kenya 2022: skipped_missing_variables — not wired on this platform: requires harmonised repeated rounds + policy timing — available via Causal.jl DiD on pooled multi-round data, not a single-survey run

J.13 M. Multilevel, Spatial and Small-Area Models — 7 cards, 2 complete on the pilot

J.13.79 Cluster random-intercept health model

Table 283: Cluster random-intercept health model

Purpose	Estimate, explain or predict health outcome with community heterogeneity using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	health outcome with community heterogeneity.
Core specification	g(E[Y_ic])=X_icβ+u_c
Key inputs	individual/household variables and cluster ID.
Estimation or simulation	multilevel GLMM.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	ICC, random-effect distribution. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	cluster-adjusted effects and ICC. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	community-level targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/multilevel_spatial/cluster_random_intercept_health_model.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.13.80 Region/district hierarchical model

Table 284: Region/district hierarchical model

Purpose	Estimate, explain or predict outcome with higher-level heterogeneity using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	outcome with higher-level heterogeneity.
Core specification	g(E[Y_ij])=X_ijβ+u_j
Key inputs	DHS outcome, region/district.
Estimation or simulation	hierarchical model.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	variance partition and shrinkage checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	area effects. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	subnational planning. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/multilevel_spatial/region_district_hierarchical_model.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.13.81 Spatial Gaussian process prevalence model

Table 285: Spatial Gaussian process prevalence model

Purpose	Estimate, explain or predict continuous spatial risk surface using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	continuous spatial risk surface.
Core specification	g(p(s))=X(s)β+w(s), w~GP(0,Cθ)
Key inputs	DHS cluster prevalence, GPS, covariates.
Estimation or simulation	Bayesian geostatistical model.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	spatial CV, variogram/range checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	risk surfaces with uncertainty. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	GIS health intelligence. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/multilevel_spatial/spatial_gaussian_process_prevalence_model.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: requires Bayesian geostatistics (R-INLA/SPDE) — native BYM/CAR available via SpatialModels.jl + run_spatial_adjacency.jl; Kenya 2022: skipped_missing_variables — not wired on this platform: requires Bayesian geostatistics (R-INLA/SPDE) — native BYM/CAR available via SpatialModels.jl + run_spatial_adjacency.jl

J.13.82 Bayesian small-area prevalence

Table 286: Bayesian small-area prevalence

Purpose	Estimate, explain or predict area prevalence borrowing strength using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	area prevalence borrowing strength.
Core specification	logit(p_j)=X_jβ+u_j+v_j
Key inputs	DHS direct estimates plus auxiliary area covariates.
Estimation or simulation	area-level Bayesian SAE.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	posterior predictive checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	district prevalence with credible intervals. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	fills local planning gaps. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/multilevel_spatial/bayesian_small_area_prevalence.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: area-level SAE is implemented via SmallAreaEstimation.jl (Fay-Herriot) + run_africa_sae_forecast.jl — operates on aggregated regional inputs, not a per-model unit run; Kenya 2022: skipped_missing_variables — not wired on this platform: area-level SAE is implemented via SmallAreaEstimation.jl (Fay-Herriot) + run_africa_sae_forecast.jl — operates on aggregated regional inputs, not a per-model unit run

J.13.83 Unit-level small-area model

Table 287: Unit-level small-area model

Purpose	Estimate, explain or predict individual DHS outcome plus census covariates using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	individual DHS outcome plus census covariates.
Core specification	g(E[Y_ij])=X_ijβ+u_j
Key inputs	DHS microdata + harmonized census/satellite covariates.
Estimation or simulation	unit-level SAE.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	out-of-sample area validation. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	fine-area indicators. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	continental health maps. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/multilevel_spatial/unit_level_small_area_model.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: requires harmonised census/satellite auxiliary covariates not present in this cache; Kenya 2022: skipped_missing_variables — not wired on this platform: requires harmonised census/satellite auxiliary covariates not present in this cache

J.13.84 Spatially varying coefficient model

Table 288: Spatially varying coefficient model

Purpose	Estimate, explain or predict effect heterogeneity over space using DHS micro-data in a form suitable for policy analysis and EDIS integration.
Outcome	effect heterogeneity over space.
Core specification	g(p(s))=β_0(s)+Σ_kβ_k(s)X_k
Key inputs	DHS GPS and covariates.
Estimation or simulation	Bayesian spatial varying coefficients.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	spatial CV and complexity checks. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	maps of effect heterogeneity. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	locally tailored interventions. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/multilevel_spatial/spatially_varying_coefficient_model.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: requires Bayesian spatially-varying coefficients (R-INLA/SPDE) — not on this host; Kenya 2022: skipped_missing_variables — not wired on this platform: requires Bayesian spatially-varying coefficients (R-INLA/SPDE) — not on this host

J.13.85 DHS cluster accessibility-health model

Table 289: DHS cluster accessibility-health model

Purpose	Estimate, explain or predict health outcome linked to modeled facility travel time using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	health outcome linked to modeled facility travel time.
Core specification	Pr(Y_i=1)=F(βT_c+X_iγ)
Key inputs	DHS GPS cluster, travel-time surface, health outcome.
Estimation or simulation	survey/multilevel regression.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	GPS displacement sensitivity buffers. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	access-health gradient. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	transport-health investment bridge. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/multilevel_spatial/dhs_cluster_accessibility_health_model.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: requires cluster travel-time (GE GPS + facility register) merged to the outcome cohort — travel time computed by run_gis_access.jl; merge-to-outcome not yet wired; Kenya 2022: skipped_missing_variables — not wired on this platform: requires cluster travel-time (GE GPS + facility register) merged to the outcome cohort — travel time computed by run_gis_access.jl; merge-to-outcome not yet wired

J.14 N. Prediction, Microsimulation and Bridge Models — 12 cards, 5 complete on the pilot

J.14.86 Random-forest health-risk model

Table 290: Random-forest health-risk model

Purpose	Estimate, explain or predict predict selected DHS health outcome using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	predict selected DHS health outcome.
Core specification	$\hat{Y}$_i=RF(X_i)
Key inputs	harmonized DHS predictors.
Estimation or simulation	survey-aware resampling/weighted RF where feasible.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	nested CV, calibration, subgroup performance. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	individual/cluster risk scores. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	AI risk stratification. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/prediction_bridge/random_forest_health_risk_model.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: random-forest risk models run via Prediction.jl/ml_predict (grouped-CV AUROC/Brier/calibration) as a dedicated ML pipeline, not the design-based per-model engine; Kenya 2022: skipped_missing_variables — not wired on this platform: random-forest risk models run via Prediction.jl/ml_predict (grouped-CV AUROC/Brier/calibration) as a dedicated ML pipeline, not the design-based per-model engine

J.14.87 Gradient-boosted health-risk model

Table 291: Gradient-boosted health-risk model

Purpose	Estimate, explain or predict predict selected outcome using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	predict selected outcome.
Core specification	$\hat{Y}$_i=Σ_m η f_m(X_i)
Key inputs	DHS predictors.
Estimation or simulation	XGBoost/LightGBM/CatBoost equivalent.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	nested CV, calibration, SHAP stability. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	risk probabilities and feature attribution. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	predictive layer for decision support. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/prediction_bridge/gradient_boosted_health_risk_model.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: gradient boosting runs via Prediction.jl/gradient_boost with grouped-CV tuning + SHAP — dedicated ML pipeline; Kenya 2022: skipped_missing_variables — not wired on this platform: gradient boosting runs via Prediction.jl/gradient_boost with grouped-CV tuning + SHAP — dedicated ML pipeline

J.14.88 Super learner/stacked ensemble

Table 292: Super learner/stacked ensemble

Purpose	Estimate, explain or predict combine candidate predictive models using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	combine candidate predictive models.
Core specification	$\hat{Y}$_i=Σ_m α_m $\hat{Y}$_{im}, α_m≥0
Key inputs	predictions from validated base learners.
Estimation or simulation	cross-validated stacking.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	out-of-fold performance. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	ensemble risk estimates. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	robust predictive service. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/prediction_bridge/super_learner_stacked_ensemble.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: cross-validated stacking of base learners — not yet wired (base learners available via Prediction.jl); Kenya 2022: skipped_missing_variables — not wired on this platform: cross-validated stacking of base learners — not yet wired (base learners available via Prediction.jl)

J.14.89 DHS health vulnerability index

Table 293: DHS health vulnerability index

Purpose	Estimate, explain or predict multidimensional household/individual vulnerability using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	multidimensional household/individual vulnerability.
Core specification	V_i=Σ_k ω_k z_{ik}
Key inputs	nutrition, morbidity, WASH, wealth, maternal care, demographics.
Estimation or simulation	PCA/factor or transparent normative weights.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	weight sensitivity and construct validity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	vulnerability score/quintiles. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	cross-sector targeting. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/prediction_bridge/dhs_health_vulnerability_index.jl`
Run status	Uganda 2016: complete, n = 19,588; Kenya 2022: complete, n = 37,911

J.14.90 Household health microsimulation

Table 294: Household health microsimulation

Purpose	Estimate, explain or predict simulate policy-induced probability changes using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	simulate policy-induced probability changes.
Core specification	Y_i^{s}~Bernoulli(p_i^{s}), logit(p_i^{s})=X_i^{s}β
Key inputs	estimated DHS model coefficients and scenario shocks.
Estimation or simulation	static probabilistic microsimulation.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	zero-shock reproduction, Monte Carlo error. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	counterfactual cases/coverage by subgroup. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	policy scenario engine. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/prediction_bridge/household_health_microsimulation.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.14.91 Maternal-child intervention microsimulation

Table 295: Maternal-child intervention microsimulation

Purpose	Estimate, explain or predict jointly simulate ANC/SBA/PNC and child outcomes using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	jointly simulate ANC/SBA/PNC and child outcomes.
Core specification	p_{ki}^{s}=F(X_{ki}^{s}β_k)
Key inputs	linked estimated model cards.
Estimation or simulation	sequential microsimulation.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	pathway consistency and uncertainty propagation. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	intervention cascade outcomes. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	health package comparison. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/prediction_bridge/maternal_child_intervention_microsimulation.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: sequential cascade microsimulation across linked cards — orchestrated via run_extended.jl scenarios, not a single-cohort run; Kenya 2022: skipped_missing_variables — not wired on this platform: sequential cascade microsimulation across linked cards — orchestrated via run_extended.jl scenarios, not a single-cohort run

J.14.92 Climate-health DHS bridge

Table 296: Climate-health DHS bridge

Purpose	Estimate, explain or predict translate climate exposures into health-risk shifts using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	translate climate exposures into health-risk shifts.
Core specification	Δlogit(p_i)=β_C ΔClimate_c
Key inputs	DHS health outcome + externally matched climate exposure.
Estimation or simulation	multilevel/spatial regression then scenario transfer.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	exposure-window and GPS displacement sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	climate-attributable risk changes. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	EDIS climate module. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/prediction_bridge/climate_health_dhs_bridge.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: requires cluster-matched climate exposure (CHIRPS/temperature rasters) — blocked by the GDAL/SAC raster wall on this host; Kenya 2022: skipped_missing_variables — not wired on this platform: requires cluster-matched climate exposure (CHIRPS/temperature rasters) — blocked by the GDAL/SAC raster wall on this host

J.14.93 Agriculture-nutrition DHS bridge

Table 297: Agriculture-nutrition DHS bridge

Purpose	Estimate, explain or predict translate food/agricultural shocks into nutrition outcomes using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	translate food/agricultural shocks into nutrition outcomes.
Core specification	ΔY_i=β_F ΔFoodSecurity_i + . . .
Key inputs	DHS nutrition plus food/agriculture exposure proxies.
Estimation or simulation	regression/microsimulation bridge.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	mediation and external-variable caveats. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	nutrition impacts of food shocks. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	agriculture-health integration. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/prediction_bridge/agriculture_nutrition_dhs_bridge.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: requires food-security / agricultural exposure proxies not collected in standard DHS; Kenya 2022: skipped_missing_variables — not wired on this platform: requires food-security / agricultural exposure proxies not collected in standard DHS

J.14.94 Education-health DHS bridge

Table 298: Education-health DHS bridge

Purpose	Estimate, explain or predict estimate health returns to maternal/household education using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	estimate health returns to maternal/household education.
Core specification	g(E[Y_i])=β_E Edu_i+X_iγ
Key inputs	DHS education and health outcomes.
Estimation or simulation	survey regression/causal option where justified.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	confounding sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	education-health elasticities. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	education-human-capital integration. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/prediction_bridge/education_health_dhs_bridge.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.14.95 Health-to-labour productivity bridge

Table 299: Health-to-labour productivity bridge

Purpose	Estimate, explain or predict map DHS morbidity/nutrition states to productivity parameters using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	map DHS morbidity/nutrition states to productivity parameters.
Core specification	Prod_f^s=Prod_f^0(1+φ_f ΔHealth_f)
Key inputs	DHS health prevalence by working-age group plus literature/linked earnings evidence.
Estimation or simulation	bridge calibration with sensitivity ranges.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	unit consistency and scenario sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	health-adjusted labour productivity. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	CDCGE factor-productivity shocks. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/prediction_bridge/health_to_labour_productivity_bridge.jl`
Run status	Uganda 2016: skipped_missing_variables — not wired on this platform: calibration bridge to CDCGE factor productivity — implemented via CrossSectorExports.jl (health→macro), needs literature elasticities not a per-cohort fit; Kenya 2022: skipped_missing_variables — not wired on this platform: calibration bridge to CDCGE factor productivity — implemented via CrossSectorExports.jl (health→macro), needs literature elasticities not a per-cohort fit

J.14.96 Health-to-household/CGE bridge

Table 300: Health-to-household/CGE bridge

Purpose	Estimate, explain or predict map health indicators to representative households/factors using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	map health indicators to representative households/factors.
Core specification	H_{h,f}=Σ_i w_i 1(i∈h,f)Y_i / Σ_i w_i1(i∈h,f)
Key inputs	DHS outcomes, household/skill/geography crosswalks.
Estimation or simulation	weighted aggregation and crosswalk.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	share reconciliation and coverage. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	health prevalence matrices by CGE household/factor. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	CDCGE distributional integration. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/prediction_bridge/health_to_household_cge_bridge.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.14.97 Health policy targeting score

Table 301: Health policy targeting score

Purpose	Estimate, explain or predict rank households/areas by expected benefit or risk using DHS microdata in a form suitable for policy analysis and EDIS integration.
Outcome	rank households/areas by expected benefit or risk.
Core specification	Score_i=E[Benefit_i|X_i]-λCost_i
Key inputs	validated DHS risk models and policy eligibility.
Estimation or simulation	decision rule/optimization-ready score.
Survey-design treatment	Use DHS sampling weights and design variables where the estimator supports them. For multilevel, spatial or machine-learning estimators that cannot reproduce the full complex design directly, document the approximation and use defensible cluster-robust, bootstrap or design-aware resampling.
Diagnostics and validation	fairness, calibration, threshold sensitivity. Always report effective sample size, missingness, convergence/fit status, uncertainty and weighted observed-versus-predicted checks.
Primary outputs	priority lists and coverage curves. Export coefficients/parameters, uncertainty, marginal effects or predictions, subgroup summaries and a machine-readable model card.
EDIS integration	feeds EDIS resource-allocation optimization. Outputs should be interoperable with the EDIS Health System and wider sector modules through CSV/Arrow/Parquet and documented bridge tables.
Policy scenarios	Where structurally meaningful, simulate changes in modifiable determinants while holding non-policy covariates fixed. Label association-based simulations separately from causally identified effects.
Implementation notes	Maintain a country/survey configuration rather than hard-coded DHS variable names. Validate recodes against DHS labels and questionnaire metadata. Refuse estimation when required variables, eligible sample or survey-design metadata are absent.
Implemented in	`src/Models/prediction_bridge/health_policy_targeting_score.jl`
Run status	Uganda 2016: complete, n = 4,423; Kenya 2022: complete, n = 17,327

J.15 What this register is for

Three uses. First, to check a claim: if someone quotes a number from this estate, the card behind it names the outcome, the denominator and the design treatment, and you can check all three against what was said. Second, to plan a run: the inputs field tells you what a survey must carry before the card can run at all, which is the question Laboratory 01 asks. Third, to escalate: a card whose specification is sound and whose data exist but which is not wired on your platform is a deployment problem with an owner, and this is where you establish that.

The same content is shipped as `08_Data/model_cards.csv`, one row per card and one column per field, so it can be filtered and joined rather than read. Of the 97 cards, 61 ran on Uganda 2016 DHS (UG2016DHS) and 55 on Kenya 2022 DHS (KE2022DHS); every skip names what was missing.

Appendix K. The committed estimates

Every design-based estimate the two committed runs produced: 336 cells on Uganda 2016 DHS (UG2016DHS) and 602 on Kenya 2022 DHS (KE2022DHS). The chapters quote these tables a few rows at a time; this appendix carries them whole, so that any claim made anywhere in this course can be checked against the run without opening a spreadsheet.

READ THE LAST TWO COLUMNS FIRST

deff is the design effect. Divide the unweighted n by it to get the effective sample size — the simple random sample that would have carried the same information. A cell with a deff near 3 has thrown away two thirds of its interviews to clustering.

Rel. is the disclosure decision. `NO` means the cell was suppressed and must not be reported, reconstructed by subtraction from released cells, or inferred from a neighbouring table. Some suppressed cells clear the unweighted threshold: that is secondary suppression, and Chapter 39 gives the rule.

K.1 Uganda 2016 DHS (UG2016DHS)

Table 302: All 336 cells, Uganda 2016 DHS (UG2016DHS)

Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
Anaemia in children 6-59 months	National	all	53.76 %	51.49 % - 56.04 %	2.13	3,944	yes
	Residence	rural	55.16 %	52.66 % - 57.66 %	2.16	3,275	yes
	Residence	urban	48.46 %	43.19 % - 53.73 %	1.93	669	yes
	Wealth quintile	1	66.83 %	63.29 % - 70.36 %	1.55	1,056	yes
	Wealth quintile	2	56.26 %	52.33 % - 60.18 %	1.37	842	yes
	Wealth quintile	3	48.52 %	44.03 % - 53.02 %	1.64	776	yes
	Wealth quintile	4	48.52 %	43.73 % - 53.31 %	1.63	681	yes
	Wealth quintile	5	46.10 %	40.69 % - 51.51 %	1.81	589	yes
	Mother's education	higher	41.36 %	34.83 % - 47.88 %	0.90	196	yes
	Mother's education	none	62.21 %	56.90 % - 67.53 %	1.61	515	yes
	Mother's education	primary	54.06 %	51.25 % - 56.87 %	2.08	2,510	yes
	Mother's education	secondary	52.01 %	47.70 % - 56.31 %	1.40	723	yes
	Region	acholi	70.13 %	63.68 % - 76.58 %	1.24	240	yes
	Region	ankole	31.30 %	23.52 % - 39.08 %	1.88	257	yes
	Region	bugisu	50.38 %	42.11 % - 58.66 %	1.37	192	yes
	Region	bukedi	49.49 %	42.86 % - 56.12 %	1.34	292	yes
	Region	bunyoro	57.57 %	48.09 % - 67.06 %	2.66	277	yes
	Region	busoga	63.19 %	54.46 % - 71.93 %	3.01	352	yes
	Region	kampala	52.83 %	42.37 % - 63.29 %	1.65	144	yes
	Region	karamoja	67.09 %	58.56 % - 75.62 %	1.75	204	yes
	Region	kigezi	34.01 %	25.01 % - 43.02 %	1.55	165	yes
	Region	lango	63.64 %	55.68 % - 71.59 %	2.02	283	yes
	Region	north buganda	55.05 %	48.07 % - 62.02 %	1.62	316	yes
	Region	south buganda	53.84 %	45.81 % - 61.86 %	2.07	307	yes
	Region	teso	59.41 %	53.00 % - 65.82 %	1.34	303	yes
	Region	tooro	44.90 %	36.57 % - 53.24 %	2.46	336	yes
	Region	west nile	57.20 %	48.31 % - 66.09 %	2.32	276	yes
	Sex of child	female	52.28 %	49.42 % - 55.15 %	1.68	1,961	yes
	Sex of child	male	55.22 %	52.27 % - 58.17 %	1.82	1,983	yes
Four or more antenatal visits	National	all	60.22 %	58.81 % - 61.64 %	2.23	10,219	yes
	Residence	rural	58.48 %	56.84 % - 60.12 %	2.36	8,195	yes
	Residence	urban	66.08 %	63.42 % - 68.74 %	1.66	2,024	yes
	Wealth quintile	1	53.91 %	50.78 % - 57.04 %	2.60	2,534	yes
	Wealth quintile	2	57.42 %	54.82 % - 60.02 %	1.58	2,197	yes
	Wealth quintile	3	59.29 %	56.36 % - 62.22 %	1.79	1,938	yes
	Wealth quintile	4	63.12 %	60.41 % - 65.82 %	1.44	1,763	yes
	Wealth quintile	5	67.49 %	64.73 % - 70.25 %	1.62	1,787	yes

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Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Mother's education	higher	73.95 %	70.20 % - 77.70 %	1.15	603	yes
	Mother's education	none	53.59 %	49.97 % - 57.20 %	1.75	1,280	yes
	Mother's education	primary	57.76 %	56.01 % - 59.51 %	2.05	6,268	yes
	Mother's education	secondary	65.68 %	63.29 % - 68.08 %	1.37	2,068	yes
	Region	acholi	60.92 %	55.14 % - 66.70 %	2.28	625	yes
	Region	ankole	68.13 %	62.77 % - 73.49 %	2.43	704	yes
	Region	bugisu	47.02 %	40.09 % - 53.95 %	2.60	518	yes
	Region	bukedi	54.70 %	48.92 % - 60.48 %	2.49	709	yes
	Region	bunyoro	44.54 %	37.23 % - 51.85 %	3.90	692	yes
	Region	busoga	66.11 %	62.34 % - 69.87 %	1.42	863	yes
	Region	kampala	66.91 %	61.66 % - 72.16 %	1.70	525	yes
	Region	karamoja	66.02 %	59.84 % - 72.21 %	2.22	501	yes
	Region	kigezi	59.40 %	54.27 % - 64.53 %	1.35	474	yes
	Region	lango	55.92 %	50.58 % - 61.26 %	2.08	689	yes
	Region	north buganda	57.60 %	52.91 % - 62.28 %	1.91	817	yes
	Region	south buganda	64.79 %	60.62 % - 68.96 %	1.66	835	yes
	Region	teso	53.43 %	48.76 % - 58.11 %	1.71	747	yes
	Region	tooro	63.98 %	60.61 % - 67.35 %	1.00	777	yes
	Region	west nile	65.25 %	60.44 % - 70.05 %	1.97	743	yes
Children ever born	National	all	3.08	3.02 - 3.14	nan	18,506	yes
	Residence	rural	3.36	3.29 - 3.44	nan	14,127	yes
	Residence	urban	2.31	2.20 - 2.41	nan	4,379	yes
	Wealth quintile	1	3.68	3.58 - 3.77	nan	3,884	yes
	Wealth quintile	2	3.47	3.37 - 3.58	nan	3,640	yes
	Wealth quintile	3	3.50	3.39 - 3.61	nan	3,485	yes
	Wealth quintile	4	3.09	2.97 - 3.21	nan	3,454	yes
	Wealth quintile	5	2.08	2.00 - 2.17	nan	4,043	yes
	Mother's education	higher	1.67	1.55 - 1.79	nan	1,329	yes
	Mother's education	none	5.84	5.66 - 6.03	nan	2,071	yes
	Mother's education	primary	3.37	3.30 - 3.43	nan	10,893	yes
	Mother's education	secondary	1.81	1.74 - 1.89	nan	4,213	yes
	Region	acholi	3.15	2.97 - 3.33	nan	1,110	yes
	Region	ankole	3.34	3.14 - 3.53	nan	1,301	yes
	Region	bugisu	3.24	3.01 - 3.47	nan	957	yes
	Region	bukedi	3.38	3.19 - 3.56	nan	1,205	yes
	Region	bunyoro	3.03	2.89 - 3.16	nan	1,213	yes
	Region	busoga	3.59	3.34 - 3.85	nan	1,530	yes
	Region	kampala	1.88	1.70 - 2.06	nan	1,300	yes
	Region	karamoja	3.48	3.23 - 3.74	nan	741	yes
	Region	kigezi	2.78	2.59 - 2.96	nan	959	yes
	Region	lango	3.29	3.13 - 3.45	nan	1,236	yes
	Region	north buganda	3.21	3.00 - 3.42	nan	1,410	yes
	Region	south buganda	2.66	2.43 - 2.89	nan	1,615	yes
	Region	teso	3.12	2.92 - 3.31	nan	1,347	yes
	Region	tooro	3.13	2.91 - 3.36	nan	1,301	yes
	Region	west nile	3.11	2.81 - 3.42	nan	1,281	yes
Delivery in a health facility	National	all	73.36 %	71.62 % - 75.11 %	6.31	15,522	yes
	Residence	rural	69.49 %	67.43 % - 71.55 %	6.64	12,711	yes
	Residence	urban	87.79 %	85.53 % - 90.04 %	3.48	2,811	yes
	Wealth quintile	1	64.23 %	61.05 % - 67.41 %	4.76	4,152	yes
	Wealth quintile	2	63.12 %	60.32 % - 65.91 %	2.95	3,382	yes
	Wealth quintile	3	70.70 %	67.90 % - 73.51 %	2.95	2,971	yes
	Wealth quintile	4	78.96 %	76.51 % - 81.41 %	2.45	2,607	yes
	Wealth quintile	5	92.68 %	91.27 % - 94.08 %	1.83	2,410	yes
	Mother's education	higher	96.26 %	94.36 % - 98.15 %	2.10	808	yes
	Mother's education	none	61.29 %	57.61 % - 64.97 %	3.09	2,080	yes
	Mother's education	primary	68.42 %	66.43 % - 70.42 %	4.65	9,705	yes
	Mother's education	secondary	87.16 %	85.38 % - 88.93 %	2.15	2,929	yes
	Region	acholi	84.13 %	80.04 % - 88.23 %	2.97	908	yes
	Region	ankole	70.58 %	64.47 % - 76.70 %	4.91	1,047	yes
	Region	bugisu	56.17 %	48.24 % - 64.10 %	5.32	800	yes
	Region	bukedi	66.00 %	60.01 % - 71.99 %	4.64	1,114	yes
	Region	bunyoro	56.86 %	46.94 % - 66.79 %	11.33	1,084	yes
	Region	busoga	76.50 %	71.67 % - 81.33 %	4.74	1,402	yes
	Region	kampala	94.34 %	92.10 % - 96.59 %	1.69	686	yes

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Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Region	karamoja	71.17 %	63.70 % - 78.65 %	6.19	873	yes
	Region	kigezi	69.68 %	62.61 % - 76.75 %	4.25	690	yes
	Region	lango	66.30 %	59.04 % - 73.56 %	5.94	968	yes
	Region	north buganda	74.70 %	68.86 % - 80.55 %	5.99	1,270	yes
	Region	south buganda	81.09 %	75.58 % - 86.59 %	6.43	1,250	yes
	Region	teso	73.86 %	67.98 % - 79.74 %	5.42	1,164	yes
	Region	tooro	73.64 %	67.83 % - 79.45 %	5.31	1,173	yes
	Region	west nile	78.20 %	72.19 % - 84.20 %	6.01	1,093	yes
	Sex of child	female	73.88 %	71.97 % - 75.79 %	3.77	7,678	yes
	Sex of child	male	72.85 %	70.91 % - 74.79 %	3.89	7,844	yes
Fever in the last two weeks	National	all	37.25 %	35.13 % - 39.37 %	2.26	4,527	yes
	Residence	rural	40.39 %	38.00 % - 42.77 %	2.31	3,763	yes
	Residence	urban	25.04 %	20.87 % - 29.22 %	1.85	764	yes
	Wealth quintile	1	50.71 %	47.25 % - 54.18 %	1.52	1,219	yes
	Wealth quintile	2	39.08 %	35.12 % - 43.03 %	1.63	955	yes
	Wealth quintile	3	35.34 %	31.17 % - 39.50 %	1.74	880	yes
	Wealth quintile	4	38.65 %	34.20 % - 43.11 %	1.70	783	yes
	Wealth quintile	5	20.47 %	16.36 % - 24.58 %	1.86	690	yes
	Mother's education	higher	24.92 %	18.89 % - 30.95 %	1.21	240	yes
	Mother's education	none	46.03 %	40.81 % - 51.25 %	1.70	594	yes
	Mother's education	primary	39.40 %	36.94 % - 41.86 %	1.89	2,861	yes
	Mother's education	secondary	30.00 %	25.82 % - 34.19 %	1.81	832	yes
	Region	acholi	54.18 %	45.94 % - 62.43 %	1.94	272	yes
	Region	ankole	18.85 %	13.75 % - 23.96 %	1.31	295	yes
	Region	bugisu	24.57 %	17.50 % - 31.64 %	1.52	217	yes
	Region	bukedi	35.50 %	28.17 % - 42.84 %	1.99	326	yes
	Region	bunyoro	7.36 %	4.18 % - 10.54 %	1.26	326	yes
	Region	busoga	70.55 %	63.94 % - 77.15 %	2.19	401	yes
	Region	kampala	16.62 %	6.99 % - 26.25 %	3.07	176	yes
	Region	karamoja	58.05 %	49.86 % - 66.25 %	1.77	247	yes
	Region	kigezi	12.85 %	6.47 % - 19.24 %	1.81	191	yes
	Region	lango	59.37 %	52.59 % - 66.14 %	1.51	306	yes
	Region	north buganda	32.68 %	25.08 % - 40.28 %	2.41	353	yes
	Region	south buganda	27.02 %	20.34 % - 33.71 %	2.10	357	yes
	Region	teso	64.35 %	57.51 % - 71.18 %	1.96	369	yes
	Region	tooro	22.21 %	14.91 % - 29.51 %	3.01	375	yes
	Region	west nile	48.75 %	43.33 % - 54.18 %	0.97	316	yes
	Sex of child	female	37.19 %	34.68 % - 39.70 %	1.57	2,239	yes
	Sex of child	male	37.32 %	34.55 % - 40.09 %	1.95	2,288	yes
Malaria, rapid diagnostic test positive	National	all	30.33 %	27.91 % - 32.75 %	3.46	4,796	yes
	Residence	rural	34.83 %	32.06 % - 37.61 %	3.52	3,991	yes
	Residence	urban	11.69 %	7.99 % - 15.40 %	2.79	805	yes
	Wealth quintile	1	52.44 %	48.34 % - 56.55 %	2.16	1,228	yes
	Wealth quintile	2	35.01 %	30.73 % - 39.30 %	2.19	1,040	yes
	Wealth quintile	3	29.58 %	25.54 % - 33.61 %	1.96	961	yes
	Wealth quintile	4	24.45 %	20.16 % - 28.75 %	2.29	879	yes
	Wealth quintile	5	4.79 %	3.10 % - 6.48 %	1.13	688	yes
	Mother's education	none	—	-	—	4,782	NO
	Mother's education	primary	—	-	—	14	NO
	Region	acholi	63.02 %	54.46 % - 71.58 %	2.40	294	yes
	Region	ankole	11.24 %	6.93 % - 15.56 %	1.50	309	yes
	Region	bugisu	19.77 %	12.08 % - 27.45 %	2.45	253	yes
	Region	bukedi	26.99 %	16.19 % - 37.80 %	5.41	351	yes
	Region	bunyoro	31.69 %	23.21 % - 40.16 %	2.80	324	yes
	Region	busoga	52.16 %	41.44 % - 62.88 %	5.63	470	yes
	Region	kampala	0.84 %	-0.43 % - 2.11 %	0.88	174	yes
	Region	karamoja	70.92 %	60.71 % - 81.14 %	3.06	232	yes
	Region	kigezi	2.80 %	0.55 % - 5.05 %	1.02	211	yes
	Region	lango	61.92 %	54.17 % - 69.67 %	2.21	333	yes
	Region	north buganda	21.75 %	14.69 % - 28.80 %	2.98	391	yes
	Region	south buganda	15.87 %	9.11 % - 22.63 %	3.40	382	yes
	Region	teso	51.70 %	41.74 % - 61.66 %	3.52	341	yes

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Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Region	tooro	18.02 %	11.77 % - 24.26 %	2.83	412	yes
	Region	west nile	24.85 %	16.65 % - 33.05 %	2.99	319	yes
Completed the maternal continuum	National	all	2.34 %	1.99 % - 2.70 %	1.48	10,219	yes
	Residence	rural	2.09 %	1.71 % - 2.46 %	1.46	8,195	yes
	Residence	urban	3.20 %	2.28 % - 4.12 %	1.43	2,024	yes
	Wealth quintile	1	2.00 %	1.42 % - 2.59 %	1.14	2,534	yes
	Wealth quintile	2	1.56 %	0.93 % - 2.19 %	1.49	2,197	yes
	Wealth quintile	3	1.64 %	0.93 % - 2.34 %	1.57	1,938	yes
	Wealth quintile	4	2.75 %	1.90 % - 3.60 %	1.25	1,763	yes
	Wealth quintile	5	3.71 %	2.66 % - 4.76 %	1.44	1,787	yes
	Mother's education	higher	5.49 %	3.29 % - 7.70 %	1.47	603	yes
	Mother's education	none	2.57 %	1.66 % - 3.48 %	1.10	1,280	yes
	Mother's education	primary	1.74 %	1.35 % - 2.13 %	1.45	6,268	yes
	Mother's education	secondary	2.87 %	2.06 % - 3.68 %	1.27	2,068	yes
	Region	acholi	2.35 %	1.17 % - 3.53 %	0.99	625	yes
	Region	ankole	0.56 %	0.03 % - 1.09 %	0.93	704	yes
	Region	bugisu	6.44 %	3.83 % - 9.04 %	1.52	518	yes
	Region	bukedi	3.14 %	1.93 % - 4.35 %	0.89	709	yes
	Region	bunyoro	1.51 %	0.26 % - 2.77 %	1.91	692	yes
	Region	busoga	2.88 %	1.51 % - 4.25 %	1.51	863	yes
	Region	kampala	2.95 %	1.23 % - 4.68 %	1.43	525	yes
	Region	karamoja	10.67 %	7.44 % - 13.90 %	1.43	501	yes
	Region	kigezi	0.22 %	-0.21 % - 0.66 %	1.05	474	yes
	Region	lango	0.95 %	-0.04 % - 1.95 %	1.89	689	yes
	Region	north buganda	1.27 %	0.39 % - 2.16 %	1.33	817	yes
	Region	south buganda	2.49 %	1.16 % - 3.82 %	1.58	835	yes
	Region	teso	1.13 %	0.14 % - 2.13 %	1.72	747	yes
	Region	tooro	3.16 %	1.71 % - 4.61 %	1.38	777	yes
	Region	west nile	1.09 %	0.32 % - 1.86 %	1.06	743	yes
Modern contraceptive use	National	all	34.76 %	33.43 % - 36.09 %	2.32	11,379	yes
	Residence	rural	32.97 %	31.42 % - 34.53 %	2.60	9,108	yes
	Residence	urban	40.56 %	38.18 % - 42.95 %	1.40	2,271	yes
	Wealth quintile	1	22.42 %	20.23 % - 24.62 %	1.88	2,615	yes
	Wealth quintile	2	32.19 %	29.99 % - 34.38 %	1.38	2,396	yes
	Wealth quintile	3	35.81 %	33.32 % - 38.31 %	1.57	2,223	yes
	Wealth quintile	4	40.20 %	37.56 % - 42.83 %	1.56	2,077	yes
	Wealth quintile	5	42.11 %	39.63 % - 44.60 %	1.36	2,068	yes
	Mother's education	higher	42.99 %	39.17 % - 46.82 %	1.15	742	yes
	Mother's education	none	22.63 %	19.77 % - 25.49 %	1.93	1,587	yes
	Mother's education	primary	34.18 %	32.59 % - 35.76 %	2.01	6,904	yes
	Mother's education	secondary	40.36 %	37.75 % - 42.97 %	1.58	2,146	yes
	Region	acholi	30.16 %	25.57 % - 34.74 %	1.73	667	yes
	Region	ankole	36.17 %	32.25 % - 40.09 %	1.47	852	yes
	Region	bugisu	43.16 %	38.59 % - 47.73 %	1.37	617	yes
	Region	bukedi	34.50 %	30.71 % - 38.29 %	1.34	809	yes
	Region	bunyoro	29.59 %	23.20 % - 35.97 %	3.79	745	yes
	Region	busoga	28.53 %	22.67 % - 34.39 %	4.37	996	yes
	Region	kampala	39.18 %	34.24 % - 44.13 %	1.55	581	yes
	Region	karamoja	6.49 %	2.13 % - 10.84 %	4.32	531	yes
	Region	kigezi	43.23 %	37.36 % - 49.09 %	2.20	602	yes
	Region	lango	41.40 %	36.41 % - 46.38 %	2.14	804	yes
	Region	north buganda	41.98 %	37.63 % - 46.33 %	1.71	846	yes
	Region	south buganda	40.34 %	36.26 % - 44.43 %	1.64	910	yes
	Region	teso	30.42 %	26.25 % - 34.59 %	1.75	819	yes
	Region	tooro	37.36 %	33.08 % - 41.65 %	1.68	822	yes
	Region	west nile	18.98 %	14.74 % - 23.22 %	2.37	778	yes
Stunting, height-for-age below -2 SD	National	all	28.16 %	26.45 % - 29.87 %	1.66	4,423	yes
	Residence	rural	29.63 %	27.69 % - 31.56 %	1.72	3,683	yes
	Residence	urban	22.39 %	18.88 % - 25.90 %	1.37	740	yes
	Wealth quintile	1	32.51 %	29.42 % - 35.61 %	1.35	1,187	yes
	Wealth quintile	2	32.31 %	28.33 % - 36.29 %	1.77	936	yes
	Wealth quintile	3	31.59 %	27.99 % - 35.19 %	1.36	868	yes
	Wealth quintile	4	26.56 %	22.49 % - 30.64 %	1.70	768	yes

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continued

Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Wealth quintile	5	16.63 %	13.39 % - 19.87 %	1.31	664	yes
	Mother's education	higher	9.74 %	5.26 % - 14.22 %	1.37	230	yes
	Mother's education	none	37.81 %	32.77 % - 42.86 %	1.61	573	yes
	Mother's education	primary	30.10 %	27.93 % - 32.28 %	1.64	2,807	yes
	Mother's education	secondary	22.94 %	19.36 % - 26.53 %	1.54	813	yes
	Region	acholi	30.69 %	24.54 % - 36.84 %	1.25	270	yes
	Region	ankole	29.18 %	23.02 % - 35.33 %	1.38	289	yes
	Region	bugisu	36.29 %	28.04 % - 44.54 %	1.57	205	yes
	Region	bukedi	20.65 %	15.21 % - 26.09 %	1.53	326	yes
	Region	bunyoro	35.76 %	29.70 % - 41.83 %	1.32	316	yes
	Region	busoga	26.89 %	19.95 % - 33.84 %	2.56	400	yes
	Region	kampala	17.63 %	11.62 % - 23.65 %	1.06	163	yes
	Region	karamoja	34.94 %	28.26 % - 41.62 %	1.15	225	yes
	Region	kigezi	29.15 %	21.23 % - 37.06 %	1.50	190	yes
	Region	lango	21.99 %	17.79 % - 26.18 %	0.80	300	yes
	Region	north buganda	26.99 %	20.81 % - 33.17 %	1.75	347	yes
	Region	south buganda	25.77 %	20.54 % - 31.00 %	1.28	345	yes
	Region	teso	13.02 %	9.06 % - 16.97 %	1.32	368	yes
	Region	tooro	40.42 %	34.21 % - 46.62 %	1.54	370	yes
	Region	west nile	34.34 %	27.50 % - 41.18 %	1.67	309	yes
	Sex of child	female	26.45 %	24.37 % - 28.54 %	1.28	2,196	yes
	Sex of child	male	29.84 %	27.53 % - 32.16 %	1.48	2,227	yes
Survival to age five	National	all	1.35 %	1.26 % - 1.43 %	1.94	143,471	yes
	Residence	rural	1.41 %	1.32 % - 1.50 %	1.78	117,727	yes
	Residence	urban	1.13 %	0.93 % - 1.33 %	2.39	25,744	yes
	Wealth quintile	1	1.65 %	1.47 % - 1.83 %	1.88	37,874	yes
	Wealth quintile	2	1.45 %	1.28 % - 1.62 %	1.58	31,276	yes
	Wealth quintile	3	1.31 %	1.15 % - 1.47 %	1.49	28,513	yes
	Wealth quintile	4	1.30 %	1.13 % - 1.47 %	1.48	24,253	yes
	Wealth quintile	5	0.96 %	0.79 % - 1.14 %	1.83	21,555	yes
	Mother's education	higher	0.57 %	0.35 % - 0.79 %	1.46	6,664	yes
	Mother's education	none	1.87 %	1.64 % - 2.11 %	1.81	23,098	yes
	Mother's education	primary	1.41 %	1.31 % - 1.51 %	1.72	90,366	yes
	Mother's education	secondary	0.97 %	0.81 % - 1.12 %	1.52	23,343	yes
	Region	acholi	1.22 %	0.91 % - 1.54 %	1.96	9,050	yes
	Region	ankole	1.27 %	1.01 % - 1.54 %	1.57	10,542	yes
	Region	bugisu	1.18 %	0.90 % - 1.45 %	1.27	7,630	yes
	Region	bukedi	1.37 %	1.13 % - 1.61 %	1.11	10,072	yes
	Region	bunyoro	1.74 %	1.36 % - 2.11 %	1.99	9,242	yes
	Region	busoga	1.53 %	1.26 % - 1.80 %	1.67	13,119	yes
	Region	kampala	1.24 %	0.74 % - 1.75 %	3.15	5,921	yes
	Region	karamoja	1.93 %	1.55 % - 2.31 %	1.53	7,684	yes
	Region	kigezi	1.15 %	0.84 % - 1.46 %	1.43	6,511	yes
	Region	lango	1.21 %	0.96 % - 1.46 %	1.34	9,655	yes
	Region	north buganda	1.36 %	1.01 % - 1.71 %	2.66	11,483	yes
	Region	south buganda	1.14 %	0.86 % - 1.41 %	2.00	11,227	yes
	Region	teso	0.98 %	0.77 % - 1.18 %	1.19	10,616	yes
	Region	tooro	1.53 %	1.26 % - 1.81 %	1.38	10,584	yes
	Region	west nile	1.58 %	1.23 % - 1.92 %	2.04	10,135	yes
	Sex of child	female	1.19 %	1.09 % - 1.29 %	1.57	71,860	yes
	Sex of child	male	1.51 %	1.39 % - 1.62 %	1.62	71,611	yes
Wasting, weight-for-height below -2 SD	National	all	3.76 %	3.11 % - 4.41 %	1.33	4,413	yes
	Residence	rural	3.96 %	3.23 % - 4.69 %	1.34	3,673	yes
	Residence	urban	2.97 %	1.60 % - 4.35 %	1.26	740	yes
	Wealth quintile	1	5.98 %	4.32 % - 7.63 %	1.50	1,188	yes
	Wealth quintile	2	4.23 %	2.71 % - 5.75 %	1.38	933	yes
	Wealth quintile	3	3.43 %	2.15 % - 4.71 %	1.11	863	yes
	Wealth quintile	4	2.20 %	0.99 % - 3.41 %	1.36	768	yes
	Wealth quintile	5	2.43 %	1.23 % - 3.63 %	1.05	661	yes
	Mother's education	higher	3.81 %	1.10 % - 6.53 %	1.20	229	yes
	Mother's education	none	4.21 %	2.05 % - 6.37 %	1.73	574	yes
	Mother's education	primary	4.00 %	3.19 % - 4.82 %	1.26	2,800	yes
	Mother's education	secondary	2.77 %	1.36 % - 4.19 %	1.57	810	yes
	Region	acholi	4.77 %	2.28 % - 7.26 %	0.96	269	yes

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continued

Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Region	ankole	2.15 %	0.52 % - 3.78 %	0.95	290	yes
	Region	bugisu	4.62 %	1.70 % - 7.53 %	1.02	204	yes
	Region	bukedi	2.42 %	0.80 % - 4.03 %	0.94	326	yes
	Region	bunyoro	2.72 %	0.14 % - 5.30 %	2.07	316	yes
	Region	busoga	3.60 %	1.67 % - 5.53 %	1.11	399	yes
	Region	kampala	4.43 %	1.20 % - 7.67 %	1.06	164	yes
	Region	karamoja	11.48 %	3.89 % - 19.08 %	3.35	227	yes
	Region	kigezi	3.97 %	0.89 % - 7.06 %	1.24	190	yes
	Region	lango	5.03 %	2.15 % - 7.91 %	1.36	300	yes
	Region	north buganda	2.70 %	0.20 % - 5.20 %	2.15	347	yes
	Region	south buganda	0.92 %	-0.39 % - 2.22 %	1.69	345	yes
	Region	teso	2.48 %	0.83 % - 4.13 %	1.08	367	yes
	Region	tooro	3.32 %	1.72 % - 4.92 %	0.77	372	yes
	Region	west nile	11.11 %	7.17 % - 15.05 %	1.21	297	yes
	Sex of child	female	3.06 %	2.29 % - 3.82 %	1.12	2,185	yes
	Sex of child	male	4.45 %	3.44 % - 5.46 %	1.39	2,228	yes
Zero-dose child	National	all	5.51 %	3.66 % - 7.35 %	1.62	953	yes
	Residence	rural	5.63 %	3.62 % - 7.63 %	1.54	781	yes
	Residence	urban	5.07 %	0.58 % - 9.56 %	1.88	172	yes
	Wealth quintile	1	3.57 %	1.09 % - 6.06 %	1.21	261	yes
	Wealth quintile	2	8.14 %	3.38 % - 12.90 %	1.70	215	yes
	Wealth quintile	3	5.54 %	1.85 % - 9.23 %	1.20	177	yes
	Wealth quintile	4	6.90 %	2.21 % - 11.59 %	1.36	153	yes
	Wealth quintile	5	3.51 %	-0.75 % - 7.78 %	2.05	147	yes
	Mother's education	higher	1.79 %	-1.72 % - 5.29 %	0.95	52	yes
	Mother's education	none	13.95 %	5.73 % - 22.18 %	1.53	104	yes
	Mother's education	primary	4.85 %	2.71 % - 7.00 %	1.58	609	yes
	Mother's education	secondary	4.87 %	0.53 % - 9.21 %	1.99	188	yes
	Region	acholi	1.05 %	-1.01 % - 3.11 %	0.56	53	yes
	Region	ankole	2.78 %	-2.59 % - 8.14 %	1.25	45	yes
	Region	bugisu	—	-	—	49	NO
	Region	bukedi	4.13 %	-0.43 % - 8.69 %	0.82	60	yes
	Region	bunyoro	9.15 %	1.28 % - 17.02 %	1.26	65	yes
	Region	busoga	10.20 %	0.58 % - 19.82 %	2.34	89	yes
	Region	kampala	4.17 %	-1.16 % - 9.50 %	0.87	47	yes
	Region	karamoja	1.04 %	-1.18 % - 3.27 %	0.80	64	yes
	Region	kigezi	—	-	—	34	NO
	Region	lango	4.15 %	-1.49 % - 9.80 %	1.25	60	yes
	Region	north buganda	9.19 %	2.71 % - 15.66 %	1.02	78	yes
	Region	south buganda	11.41 %	2.42 % - 20.40 %	1.62	78	yes
	Region	teso	1.27 %	-1.22 % - 3.77 %	1.02	79	yes
	Region	tooro	5.62 %	1.02 % - 10.22 %	0.86	83	yes
	Region	west nile	0.65 %	-0.65 % - 1.94 %	0.47	69	yes
	Sex of child	female	5.04 %	2.28 % - 7.80 %	1.90	460	yes
	Sex of child	male	5.93 %	3.31 % - 8.56 %	1.59	493	yes

Notes: Source: Uganda 2016 DHS (UG2016DHS), committed run.

K.2 Kenya 2022 DHS (KE2022DHS)

The same estimator on a different survey. Two indicators are absent because the second survey does not carry the variables they require — which is the catalogue contract in Appendix B showing up in the estimates.

Table 303: All 602 cells, Kenya 2022 DHS (KE2022DHS)

Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
Four or more antenatal visits	National	all	67.42 %	65.98 % - 68.86 %	2.56	10,401	yes
	Residence	rural	62.36 %	60.85 % - 63.86 %	1.71	6,808	yes
	Residence	urban	75.93 %	73.31 % - 78.55 %	3.52	3,593	yes
	Wealth quintile	1	54.43 %	52.05 % - 56.81 %	1.93	3,256	yes
	Wealth quintile	2	60.57 %	57.99 % - 63.14 %	1.27	1,761	yes
	Wealth quintile	3	66.43 %	63.65 % - 69.21 %	1.65	1,823	yes
	Wealth quintile	4	70.38 %	67.28 % - 73.48 %	2.46	2,044	yes
	Wealth quintile	5	83.79 %	80.92 % - 86.65 %	2.39	1,517	yes
	Mother's education	higher	83.50 %	80.90 % - 86.10 %	1.94	1,524	yes
	Mother's education	none	49.78 %	46.06 % - 53.49 %	3.02	2,101	yes
	Mother's education	primary	61.14 %	58.88 % - 63.40 %	1.96	3,502	yes
	Mother's education	secondary	69.45 %	67.45 % - 71.45 %	1.61	3,274	yes
	Region	baringo	51.34 %	41.51 % - 61.17 %	2.33	231	yes
	Region	bomet	55.98 %	49.28 % - 62.68 %	1.02	214	yes
	Region	bungoma	71.59 %	65.62 % - 77.56 %	1.14	250	yes
	Region	busia	71.64 %	65.11 % - 78.18 %	1.31	239	yes
	Region	elgeyo-marakwet	53.53 %	44.48 % - 62.59 %	1.81	211	yes
	Region	embu	63.44 %	55.06 % - 71.81 %	1.13	144	yes
	Region	garissa	29.72 %	24.62 % - 34.82 %	0.86	264	yes
	Region	homa bay	68.07 %	59.81 % - 76.34 %	1.78	218	yes
	Region	isiolo	51.45 %	44.88 % - 58.02 %	1.13	251	yes
	Region	kajiado	80.72 %	75.05 % - 86.38 %	1.24	232	yes
	Region	kakamega	75.05 %	69.72 % - 80.37 %	0.91	232	yes
	Region	kericho	60.87 %	52.75 % - 68.99 %	1.58	219	yes
	Region	kiambu	71.16 %	63.57 % - 78.75 %	1.40	191	yes
	Region	kilifi	72.83 %	66.39 % - 79.28 %	1.10	201	yes
	Region	kirinyaga	67.31 %	58.62 % - 75.99 %	1.24	139	yes
	Region	kisii	59.71 %	50.89 % - 68.53 %	1.57	186	yes
	Region	kisumu	62.99 %	55.86 % - 70.11 %	1.37	242	yes
	Region	kitui	69.83 %	62.15 % - 77.51 %	1.31	179	yes
	Region	kwale	69.52 %	61.91 % - 77.13 %	1.60	224	yes
	Region	laikipia	63.31 %	54.92 % - 71.71 %	1.18	149	yes
	Region	lamu	71.33 %	64.83 % - 77.84 %	1.23	229	yes
	Region	machakos	75.19 %	67.06 % - 83.32 %	1.44	156	yes
	Region	makueni	75.63 %	67.74 % - 83.51 %	1.61	183	yes
	Region	mandera	38.27 %	30.80 % - 45.74 %	2.44	397	yes
	Region	marsabit	67.33 %	59.21 % - 75.45 %	2.16	277	yes
	Region	meru	46.56 %	38.17 % - 54.96 %	1.28	174	yes
	Region	migori	62.31 %	54.26 % - 70.36 %	1.97	275	yes
	Region	mombasa	70.30 %	62.40 % - 78.19 %	1.44	185	yes
	Region	murang'a	61.39 %	49.04 % - 73.75 %	2.48	148	yes
	Region	nairobi	82.56 %	76.58 % - 88.55 %	1.57	242	yes
	Region	nakuru	75.56 %	69.60 % - 81.52 %	1.19	237	yes
	Region	nandi	63.94 %	57.23 % - 70.64 %	1.01	198	yes
	Region	narok	59.11 %	52.41 % - 65.81 %	1.47	303	yes
	Region	nyamira	66.74 %	59.36 % - 74.12 %	0.88	138	yes
	Region	nyandarua	62.11 %	55.94 % - 68.29 %	0.67	158	yes
	Region	nyeri	77.77 %	71.59 % - 83.95 %	0.78	135	yes
	Region	samburu	57.00 %	48.05 % - 65.96 %	2.63	309	yes
	Region	siaya	67.43 %	61.03 % - 73.82 %	1.05	217	yes
	Region	taita taveta	64.59 %	53.19 % - 76.00 %	2.01	136	yes
	Region	tana river	63.14 %	55.41 % - 70.86 %	2.03	304	yes
	Region	tharaka-nithi	66.62 %	58.08 % - 75.15 %	1.30	152	yes
	Region	trans nzoia	67.72 %	61.54 % - 73.91 %	0.97	212	yes
	Region	turkana	59.99 %	54.20 % - 65.79 %	1.11	305	yes
	Region	uasin gishu	71.63 %	66.53 % - 76.74 %	0.75	224	yes
	Region	vihiga	81.62 %	74.96 % - 88.29 %	1.36	176	yes
	Region	wajir	43.47 %	33.99 % - 52.95 %	2.83	297	yes
	Region	west pokot	35.74 %	27.83 % - 43.65 %	2.96	418	yes
Children ever born	National	all	2.21	2.17 - 2.24	nan	32,156	yes
	Residence	rural	2.54	2.49 - 2.58	nan	19,770	yes
	Residence	urban	1.73	1.67 - 1.78	nan	12,386	yes
	Wealth quintile	1	3.17	3.10 - 3.24	nan	7,073	yes
	Wealth quintile	2	2.61	2.54 - 2.67	nan	5,742	yes

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Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Wealth quintile	3	2.31	2.25 - 2.37	nan	6,345	yes
	Wealth quintile	4	1.86	1.81 - 1.92	nan	7,160	yes
	Wealth quintile	5	1.56	1.50 - 1.62	nan	5,836	yes
	Mother's education	higher	1.34	1.28 - 1.40	nan	4,879	yes
	Mother's education	none	4.66	4.52 - 4.81	nan	3,836	yes
	Mother's education	primary	3.11	3.07 - 3.16	nan	11,807	yes
	Mother's education	secondary	1.44	1.40 - 1.47	nan	11,634	yes
	Region	baringo	2.80	2.55 - 3.04	nan	687	yes
	Region	bomet	2.42	2.23 - 2.60	nan	778	yes
	Region	bungoma	2.37	2.19 - 2.55	nan	841	yes
	Region	busia	2.62	2.42 - 2.83	nan	768	yes
	Region	elgeyo-marakwet	2.67	2.47 - 2.88	nan	591	yes
	Region	embu	2.02	1.89 - 2.14	nan	584	yes
	Region	garissa	2.93	2.63 - 3.23	nan	641	yes
	Region	homa bay	2.74	2.52 - 2.96	nan	712	yes
	Region	isiolo	2.52	2.28 - 2.76	nan	623	yes
	Region	kajiado	2.08	1.87 - 2.28	nan	660	yes
	Region	kakamega	2.35	2.18 - 2.51	nan	810	yes
	Region	kericho	2.24	2.06 - 2.42	nan	779	yes
	Region	kiambu	1.79	1.63 - 1.94	nan	668	yes
	Region	kilifi	2.41	2.16 - 2.65	nan	742	yes
	Region	kirinyaga	1.86	1.76 - 1.95	nan	605	yes
	Region	kisii	2.24	2.12 - 2.36	nan	708	yes
	Region	kisumu	2.30	2.13 - 2.46	nan	761	yes
	Region	kitui	2.37	2.04 - 2.69	nan	671	yes
	Region	kwale	2.54	2.29 - 2.80	nan	711	yes
	Region	laikipia	2.20	1.97 - 2.42	nan	576	yes
	Region	lamu	2.51	2.28 - 2.74	nan	675	yes
	Region	machakos	1.91	1.79 - 2.03	nan	699	yes
	Region	makueni	2.03	1.89 - 2.17	nan	720	yes
	Region	mandera	3.55	3.22 - 3.88	nan	723	yes
	Region	marsabit	3.07	2.86 - 3.28	nan	535	yes
	Region	meru	2.11	1.95 - 2.27	nan	602	yes
	Region	migori	3.13	2.94 - 3.32	nan	777	yes
	Region	mombasa	1.81	1.66 - 1.96	nan	749	yes
	Region	murang'a	2.02	1.86 - 2.18	nan	557	yes
	Region	nairobi	1.61	1.49 - 1.72	nan	944	yes
	Region	nakuru	2.13	1.95 - 2.31	nan	782	yes
	Region	nandi	2.17	1.83 - 2.51	nan	721	yes
	Region	narok	2.69	2.27 - 3.11	nan	744	yes
	Region	nyamira	2.36	2.23 - 2.49	nan	635	yes
	Region	nyandarua	2.32	2.18 - 2.46	nan	590	yes
	Region	nyeri	1.74	1.61 - 1.88	nan	529	yes
	Region	samburu	3.14	2.86 - 3.41	nan	615	yes
	Region	siaya	2.67	2.51 - 2.82	nan	674	yes
	Region	taita taveta	2.29	2.14 - 2.45	nan	483	yes
	Region	tana river	3.16	2.87 - 3.45	nan	641	yes
	Region	tharaka-nithi	2.22	1.92 - 2.51	nan	535	yes
	Region	trans nzoia	2.54	2.33 - 2.75	nan	713	yes
	Region	turkana	3.14	2.84 - 3.44	nan	644	yes
	Region	uasin gishu	1.84	1.66 - 2.02	nan	731	yes
	Region	vihiga	2.13	1.96 - 2.30	nan	721	yes
	Region	wajir	3.48	3.24 - 3.71	nan	745	yes
	Region	west pokot	3.41	3.08 - 3.75	nan	756	yes
Delivery in a health facility	National	all	82.04 %	80.89 % - 83.20 %	2.74	11,727	yes
	Residence	rural	76.62 %	75.13 % - 78.12 %	2.51	7,724	yes
	Residence	urban	91.31 %	89.61 % - 93.01 %	3.80	4,003	yes
	Wealth quintile	1	61.77 %	59.06 % - 64.48 %	3.11	3,843	yes
	Wealth quintile	2	81.26 %	79.12 % - 83.40 %	1.55	1,984	yes
	Wealth quintile	3	87.52 %	85.65 % - 89.40 %	1.70	2,034	yes
	Wealth quintile	4	90.44 %	88.69 % - 92.19 %	2.05	2,219	yes
	Wealth quintile	5	91.26 %	88.72 % - 93.81 %	3.49	1,647	yes
	Mother's education	higher	88.51 %	85.79 % - 91.24 %	3.13	1,641	yes

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continued

Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Mother's educa-tion	none	46.57 %	42.68 % - 50.45 %	4.04	2,563	yes
	Mother's educa-tion	primary	80.96 %	79.22 % - 82.70 %	2.01	3,940	yes
	Mother's educa-tion	secondary	89.42 %	88.12 % - 90.71 %	1.65	3,583	yes
	Region	baringo	58.84 %	46.19 % - 71.49 %	4.54	264	yes
	Region	bomet	62.21 %	55.09 % - 69.32 %	1.35	240	yes
	Region	bungoma	79.69 %	72.13 % - 87.24 %	2.53	275	yes
	Region	busia	83.92 %	78.57 % - 89.27 %	1.46	264	yes
	Region	elgeyo-marakwet	77.85 %	64.52 % - 91.19 %	6.26	233	yes
	Region	embu	84.80 %	77.90 % - 91.70 %	1.52	158	yes
	Region	garissa	59.01 %	50.32 % - 67.69 %	2.77	341	yes
	Region	homa bay	85.27 %	78.96 % - 91.58 %	2.03	246	yes
	Region	isiolo	84.52 %	76.88 % - 92.17 %	3.24	278	yes
	Region	kajiado	80.17 %	71.14 % - 89.19 %	3.37	253	yes
	Region	kakamega	89.69 %	85.55 % - 93.82 %	1.24	258	yes
	Region	kericho	90.18 %	86.11 % - 94.25 %	1.16	237	yes
	Region	kiambu	91.27 %	86.89 % - 95.66 %	1.27	203	yes
	Region	kilifi	81.79 %	75.64 % - 87.94 %	1.43	216	yes
	Region	kirinyaga	92.19 %	87.07 % - 97.31 %	1.43	151	yes
	Region	kisii	79.46 %	73.72 % - 85.19 %	1.03	196	yes
	Region	kisumu	95.37 %	92.73 % - 98.01 %	1.07	262	yes
	Region	kitui	74.68 %	66.20 % - 83.16 %	1.96	198	yes
	Region	kwale	85.32 %	78.64 % - 91.99 %	2.36	255	yes
	Region	laikipia	84.92 %	77.92 % - 91.91 %	1.63	164	yes
	Region	lamu	88.16 %	82.92 % - 93.39 %	1.83	268	yes
	Region	machakos	91.90 %	87.54 % - 96.27 %	1.13	170	yes
	Region	makueni	91.69 %	87.76 % - 95.62 %	1.07	202	yes
	Region	mandera	49.74 %	40.84 % - 58.64 %	4.26	517	yes
	Region	marsabit	59.59 %	49.04 % - 70.13 %	3.79	315	yes
	Region	meru	75.75 %	66.95 % - 84.55 %	1.99	181	yes
	Region	migori	88.92 %	85.92 % - 91.93 %	0.73	306	yes
	Region	mombasa	93.30 %	89.21 % - 97.40 %	1.52	217	yes
	Region	murang'a	83.22 %	76.34 % - 90.10 %	1.41	160	yes
	Region	nairobi	91.78 %	87.26 % - 96.30 %	1.85	262	yes
	Region	nakuru	92.66 %	89.16 % - 96.16 %	1.18	252	yes
	Region	nandi	80.99 %	74.51 % - 87.46 %	1.52	214	yes
	Region	narok	63.06 %	54.00 % - 72.11 %	3.25	355	yes
	Region	nyamira	91.80 %	86.75 % - 96.85 %	1.34	152	yes
	Region	nyandarua	95.23 %	90.78 % - 99.67 %	1.91	169	yes
	Region	nyeri	97.94 %	95.73 % - 100.15 %	0.92	145	yes
	Region	samburu	45.41 %	35.31 % - 55.50 %	3.74	350	yes
	Region	siaya	87.20 %	82.67 % - 91.72 %	1.17	244	yes
	Region	taita taveta	92.52 %	87.76 % - 97.28 %	1.26	148	yes
	Region	tana river	52.17 %	39.08 % - 65.25 %	6.41	359	yes
	Region	tharaka-nithi	74.37 %	65.74 % - 83.00 %	1.63	160	yes
	Region	trans nzoia	81.65 %	76.45 % - 86.85 %	1.07	227	yes
	Region	turkana	41.86 %	31.94 % - 51.78 %	3.63	345	yes
	Region	uasin gishu	89.68 %	84.05 % - 95.30 %	2.19	246	yes
	Region	vihiga	92.16 %	87.92 % - 96.39 %	1.23	191	yes
	Region	wajir	48.07 %	32.84 % - 63.30 %	9.38	388	yes
	Region	west pokot	53.33 %	40.04 % - 66.63 %	9.10	492	yes
	Sex of child	female	81.74 %	80.31 % - 83.16 %	2.02	5,694	yes
	Sex of child	male	82.34 %	80.95 % - 83.73 %	2.09	6,033	yes
Fever in the last two weeks	National	all	17.73 %	16.78 % - 18.68 %	2.86	17,840	yes
	Residence	rural	17.68 %	16.74 % - 18.63 %	1.91	11,942	yes
	Residence	urban	17.82 %	15.79 % - 19.85 %	4.31	5,898	yes
	Wealth quintile	1	17.22 %	15.67 % - 18.77 %	2.63	6,025	yes
	Wealth quintile	2	18.06 %	16.44 % - 19.68 %	1.43	3,089	yes
	Wealth quintile	3	17.63 %	15.88 % - 19.38 %	1.70	3,086	yes
	Wealth quintile	4	19.59 %	17.39 % - 21.79 %	2.62	3,272	yes
	Wealth quintile	5	16.31 %	13.54 % - 19.07 %	3.45	2,368	yes
	Mother's educa-tion	higher	15.68 %	13.31 % - 18.06 %	2.68	2,408	yes
	Mother's educa-tion	none	15.06 %	13.26 % - 16.87 %	2.76	4,177	yes
	Mother's educa-tion	primary	18.70 %	17.36 % - 20.04 %	1.93	6,261	yes

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Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Mother's education	secondary	18.57 %	16.96 % - 20.18 %	2.23	4,994	yes
	Region	baringo	18.16 %	13.94 % - 22.38 %	1.27	408	yes
	Region	bomet	20.45 %	15.69 % - 25.21 %	1.37	377	yes
	Region	bungoma	20.72 %	16.04 % - 25.40 %	1.36	391	yes
	Region	busia	29.10 %	23.25 % - 34.95 %	1.64	380	yes
	Region	elgeyo-marakwet	8.99 %	6.24 % - 11.74 %	0.90	373	yes
	Region	embu	11.98 %	7.25 % - 16.72 %	1.31	237	yes
	Region	garissa	6.47 %	3.98 % - 8.96 %	1.42	532	yes
	Region	homa bay	37.07 %	30.07 % - 44.07 %	2.04	373	yes
	Region	isiolo	17.81 %	12.77 % - 22.86 %	1.98	437	yes
	Region	kajiado	22.51 %	16.98 % - 28.03 %	1.75	384	yes
	Region	kakamega	24.93 %	21.55 % - 28.32 %	0.56	350	yes
	Region	kericho	4.88 %	2.69 % - 7.06 %	0.99	370	yes
	Region	kiambu	17.90 %	12.26 % - 23.54 %	1.71	303	yes
	Region	kilifi	17.03 %	11.46 % - 22.60 %	2.04	357	yes
	Region	kirinyaga	5.98 %	3.06 % - 8.90 %	0.96	242	yes
	Region	kisii	11.52 %	7.02 % - 16.02 %	1.53	296	yes
	Region	kisumu	19.44 %	15.36 % - 23.52 %	1.07	388	yes
	Region	kitui	10.24 %	4.42 % - 16.07 %	2.91	303	yes
	Region	kwale	6.18 %	3.22 % - 9.15 %	1.53	387	yes
	Region	laikipia	9.23 %	5.67 % - 12.78 %	1.02	259	yes
	Region	lamu	29.19 %	23.54 % - 34.84 %	1.58	394	yes
	Region	machakos	17.56 %	11.86 % - 23.26 %	1.46	250	yes
	Region	makueni	4.18 %	0.92 % - 7.44 %	2.02	293	yes
	Region	mandera	13.35 %	9.65 % - 17.05 %	2.64	856	yes
	Region	marsabit	7.12 %	3.07 % - 11.17 %	3.23	500	yes
	Region	meru	22.19 %	16.15 % - 28.24 %	1.43	260	yes
	Region	migori	40.82 %	34.74 % - 46.90 %	1.78	446	yes
	Region	mombasa	21.78 %	15.13 % - 28.43 %	2.11	312	yes
	Region	murang'a	16.48 %	11.21 % - 21.75 %	1.24	236	yes
	Region	nairobi	15.84 %	11.10 % - 20.59 %	1.71	389	yes
	Region	nakuru	19.92 %	14.99 % - 24.85 %	1.58	397	yes
	Region	nandi	13.61 %	8.98 % - 18.24 %	1.61	340	yes
	Region	narok	11.08 %	7.48 % - 14.69 %	1.79	522	yes
	Region	nyamira	15.96 %	11.05 % - 20.88 %	1.12	239	yes
	Region	nyandarua	9.84 %	6.14 % - 13.54 %	1.09	271	yes
	Region	nyeri	16.19 %	8.95 % - 23.43 %	2.09	208	yes
	Region	samburu	13.84 %	9.31 % - 18.38 %	2.40	534	yes
	Region	siaya	13.84 %	10.93 % - 16.75 %	0.66	358	yes
	Region	taita taveta	10.98 %	7.03 % - 14.93 %	0.99	239	yes
	Region	tana river	17.85 %	14.15 % - 21.54 %	1.41	582	yes
	Region	tharaka-nithi	32.99 %	23.83 % - 42.16 %	2.34	237	yes
	Region	trans nzoia	18.58 %	13.49 % - 23.66 %	1.48	333	yes
	Region	turkana	24.34 %	19.19 % - 29.48 %	1.97	528	yes
	Region	uasin gishu	25.35 %	20.19 % - 30.52 %	1.28	349	yes
	Region	vihiga	17.25 %	11.93 % - 22.57 %	1.47	285	yes
	Region	wajir	25.32 %	20.55 % - 30.08 %	1.91	611	yes
	Region	west pokot	8.57 %	4.74 % - 12.40 %	3.52	724	yes
	Sex of child	female	17.65 %	16.45 % - 18.85 %	2.26	8,761	yes
	Sex of child	male	17.81 %	16.57 % - 19.05 %	2.48	9,079	yes
Completed the maternal continuum	National	all	3.37 %	2.87 % - 3.87 %	2.05	10,401	yes
	Residence	rural	3.24 %	2.72 % - 3.76 %	1.53	6,808	yes
	Residence	urban	3.59 %	2.58 % - 4.59 %	2.73	3,593	yes
	Wealth quintile	1	2.23 %	1.53 % - 2.93 %	1.91	3,256	yes
	Wealth quintile	2	2.76 %	1.94 % - 3.59 %	1.16	1,761	yes
	Wealth quintile	3	3.87 %	2.89 % - 4.84 %	1.22	1,823	yes
	Wealth quintile	4	3.11 %	2.19 % - 4.04 %	1.51	2,044	yes
	Wealth quintile	5	4.84 %	3.24 % - 6.44 %	2.19	1,517	yes
	Mother's education	higher	4.99 %	3.57 % - 6.41 %	1.69	1,524	yes
	Mother's education	none	1.85 %	0.39 % - 3.30 %	6.36	2,101	yes
	Mother's education	primary	2.55 %	1.84 % - 3.26 %	1.85	3,502	yes
	Mother's education	secondary	3.70 %	2.84 % - 4.56 %	1.76	3,274	yes
	Region	baringo	3.21 %	0.83 % - 5.59 %	1.10	231	yes
	Region	bomet	1.29 %	-0.52 % - 3.10 %	1.43	214	yes

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Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Region	bungoma	3.77 %	1.20 % - 6.35 %	1.19	250	yes
	Region	busia	10.37 %	5.97 % - 14.77 %	1.30	239	yes
	Region	elgeyo-marakwet	3.29 %	0.52 % - 6.07 %	1.33	211	yes
	Region	embu	7.69 %	2.15 % - 13.24 %	1.62	144	yes
	Region	garissa	0.52 %	-0.50 % - 1.54 %	1.38	264	yes
	Region	homa bay	2.09 %	0.28 % - 3.90 %	0.91	218	yes
	Region	isiolo	2.57 %	0.60 % - 4.55 %	1.02	251	yes
	Region	kajiado	1.87 %	-0.52 % - 4.25 %	1.88	232	yes
	Region	kakamega	1.38 %	-0.16 % - 2.93 %	1.06	232	yes
	Region	kericho	7.89 %	4.13 % - 11.65 %	1.11	219	yes
	Region	kiambu	2.26 %	0.15 % - 4.37 %	1.00	191	yes
	Region	kilifi	3.15 %	0.16 % - 6.14 %	1.53	201	yes
	Region	kirinyaga	1.55 %	-0.64 % - 3.73 %	1.13	139	yes
	Region	kisii	3.60 %	0.68 % - 6.51 %	1.19	186	yes
	Region	kisumu	7.62 %	4.64 % - 10.59 %	0.79	242	yes
	Region	kitui	6.34 %	1.52 % - 11.16 %	1.83	179	yes
	Region	kwale	1.55 %	-0.08 % - 3.18 %	1.02	224	yes
	Region	laikipia	2.07 %	-0.02 % - 4.17 %	0.84	149	yes
	Region	lamu	4.29 %	1.35 % - 7.23 %	1.26	229	yes
	Region	machakos	1.15 %	-0.42 % - 2.71 %	0.88	156	yes
	Region	makueni	5.15 %	0.55 % - 9.76 %	2.07	183	yes
	Region	mandera	1.27 %	-0.59 % - 3.14 %	2.85	397	yes
	Region	marsabit	0.00 %	0.00 % - 0.00 %	nan	277	yes
	Region	meru	1.51 %	-0.43 % - 3.44 %	1.14	174	yes
	Region	migori	2.32 %	-0.29 % - 4.94 %	2.16	275	yes
	Region	mombasa	1.87 %	0.03 % - 3.71 %	0.89	185	yes
	Region	murang'a	1.90 %	-0.43 % - 4.23 %	1.12	148	yes
	Region	nairobi	4.35 %	1.71 % - 6.99 %	1.05	242	yes
	Region	nakuru	3.44 %	0.98 % - 5.90 %	1.12	237	yes
	Region	nandi	2.10 %	0.16 % - 4.05 %	0.94	198	yes
	Region	narok	2.93 %	0.82 % - 5.05 %	1.24	303	yes
	Region	nyamira	2.36 %	-0.12 % - 4.83 %	0.95	138	yes
	Region	nyandarua	0.24 %	-0.24 % - 0.72 %	0.39	158	yes
	Region	nyeri	5.46 %	0.81 % - 10.11 %	1.47	135	yes
	Region	samburu	2.77 %	0.92 % - 4.61 %	1.02	309	yes
	Region	siaya	3.34 %	0.71 % - 5.97 %	1.21	217	yes
	Region	taita taveta	5.83 %	0.36 % - 11.30 %	1.93	136	yes
	Region	tana river	1.38 %	0.06 % - 2.71 %	1.02	304	yes
	Region	tharaka-nithi	9.34 %	3.28 % - 15.40 %	1.72	152	yes
	Region	trans nzoia	2.41 %	0.27 % - 4.55 %	1.07	212	yes
	Region	turkana	3.72 %	1.80 % - 5.65 %	0.82	305	yes
	Region	uasin gishu	5.33 %	1.45 % - 9.21 %	1.74	224	yes
	Region	vihiga	4.71 %	0.60 % - 8.81 %	1.72	176	yes
	Region	wajir	1.73 %	0.13 % - 3.34 %	1.17	297	yes
	Region	west pokot	2.00 %	0.51 % - 3.50 %	1.24	418	yes
Modern contraceptive use	National	all	56.91 %	55.77 % - 58.06 %	2.54	18,312	yes
	Residence	rural	57.36 %	56.20 % - 58.51 %	1.65	11,685	yes
	Residence	urban	56.22 %	53.92 % - 58.52 %	3.71	6,627	yes
	Wealth quintile	1	43.04 %	40.71 % - 45.38 %	2.59	4,487	yes
	Wealth quintile	2	61.31 %	59.42 % - 63.21 %	1.25	3,176	yes
	Wealth quintile	3	60.36 %	58.42 % - 62.31 %	1.44	3,495	yes
	Wealth quintile	4	60.07 %	57.93 % - 62.21 %	1.97	3,952	yes
	Wealth quintile	5	57.78 %	54.72 % - 60.84 %	3.19	3,202	yes
	Mother's education	higher	58.04 %	55.29 % - 60.80 %	2.25	2,774	yes
	Mother's education	none	20.47 %	17.80 % - 23.15 %	3.47	3,038	yes
	Mother's education	primary	60.22 %	58.75 % - 61.70 %	1.73	7,340	yes
	Mother's education	secondary	60.72 %	58.82 % - 62.62 %	2.03	5,160	yes
	Region	baringo	47.69 %	39.65 % - 55.72 %	2.43	361	yes
	Region	bomet	57.76 %	51.79 % - 63.73 %	1.59	419	yes
	Region	bungoma	63.66 %	59.19 % - 68.14 %	1.03	457	yes
	Region	busia	55.40 %	50.47 % - 60.33 %	1.16	451	yes
	Region	elgeyo-marakwet	59.02 %	52.38 % - 65.66 %	1.71	361	yes
	Region	embu	75.16 %	69.80 % - 80.52 %	1.35	338	yes
	Region	garissa	11.10 %	5.87 % - 16.34 %	2.83	391	yes
	Region	homa bay	54.29 %	48.62 % - 59.96 %	1.40	416	yes

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Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Region	isiolo	28.75 %	22.36 % - 35.14 %	1.89	364	yes
	Region	kajiado	57.25 %	49.66 % - 64.85 %	2.46	401	yes
	Region	kakamega	63.36 %	58.27 % - 68.45 %	1.31	450	yes
	Region	kericho	59.96 %	55.25 % - 64.68 %	1.03	426	yes
	Region	kiambu	68.23 %	61.95 % - 74.50 %	1.70	359	yes
	Region	kilifi	44.68 %	39.15 % - 50.22 %	1.24	383	yes
	Region	kirinyaga	70.79 %	65.05 % - 76.52 %	1.33	321	yes
	Region	kisii	63.55 %	58.58 % - 68.51 %	1.11	401	yes
	Region	kisumu	56.56 %	51.11 % - 62.01 %	1.29	410	yes
	Region	kitui	62.38 %	54.77 % - 69.98 %	2.48	387	yes
	Region	kwale	34.59 %	28.54 % - 40.64 %	1.80	428	yes
	Region	laikipia	64.47 %	58.08 % - 70.87 %	1.30	280	yes
	Region	lamu	39.16 %	32.02 % - 46.31 %	2.20	394	yes
	Region	machakos	66.44 %	61.99 % - 70.88 %	0.89	387	yes
	Region	makueni	64.38 %	59.00 % - 69.76 %	1.23	375	yes
	Region	mandera	1.78 %	0.30 % - 3.26 %	1.60	488	yes
	Region	marsabit	5.62 %	2.02 % - 9.22 %	2.40	377	yes
	Region	meru	69.74 %	63.25 % - 76.23 %	1.77	341	yes
	Region	migori	54.72 %	49.17 % - 60.27 %	1.44	446	yes
	Region	mombasa	42.06 %	36.06 % - 48.06 %	1.69	439	yes
	Region	murang'a	67.25 %	61.12 % - 73.38 %	1.23	278	yes
	Region	nairobi	56.16 %	50.84 % - 61.47 %	1.46	489	yes
	Region	nakuru	66.62 %	60.80 % - 72.43 %	1.71	431	yes
	Region	nandi	59.98 %	53.93 % - 66.03 %	1.54	389	yes
	Region	narok	52.20 %	47.09 % - 57.32 %	1.21	445	yes
	Region	nyamira	64.76 %	58.49 % - 71.04 %	1.59	353	yes
	Region	nyandarua	66.67 %	60.37 % - 72.96 %	1.51	325	yes
	Region	nyeri	70.53 %	63.49 % - 77.57 %	1.66	267	yes
	Region	samburu	25.40 %	18.90 % - 31.90 %	2.41	415	yes
	Region	siaya	42.94 %	37.75 % - 48.13 %	1.05	367	yes
	Region	taita taveta	64.46 %	58.51 % - 70.40 %	1.09	271	yes
	Region	tana river	23.16 %	16.59 % - 29.73 %	2.88	456	yes
	Region	tharaka-nithi	67.94 %	62.92 % - 72.97 %	1.00	330	yes
	Region	trans nzoia	65.40 %	60.54 % - 70.27 %	1.05	385	yes
	Region	turkana	30.68 %	23.44 % - 37.92 %	2.54	396	yes
	Region	uasin gishu	62.70 %	55.47 % - 69.93 %	2.32	399	yes
	Region	vihiga	60.07 %	53.65 % - 66.49 %	1.51	337	yes
	Region	wajir	2.78 %	1.28 % - 4.29 %	0.91	420	yes
	Region	west pokot	23.22 %	13.19 % - 33.25 %	7.46	508	yes
Stunting, height-for-age below -2 SD	National	all	17.38 %	16.53 % - 18.24 %	2.30	17,327	yes
	Residence	rural	20.19 %	19.21 % - 21.17 %	1.81	11,658	yes
	Residence	urban	12.23 %	10.71 % - 13.76 %	3.21	5,669	yes
	Wealth quintile	1	27.54 %	25.84 % - 29.23 %	2.18	5,845	yes
	Wealth quintile	2	21.06 %	19.27 % - 22.85 %	1.52	3,022	yes
	Wealth quintile	3	16.24 %	14.49 % - 17.98 %	1.75	3,015	yes
	Wealth quintile	4	11.63 %	10.03 % - 13.22 %	2.04	3,164	yes
	Wealth quintile	5	9.08 %	7.16 % - 10.99 %	2.63	2,281	yes
	Mother's education	higher	8.46 %	6.69 % - 10.23 %	2.46	2,332	yes
	Mother's education	none	22.05 %	19.98 % - 24.12 %	2.61	4,010	yes
	Mother's education	primary	22.05 %	20.62 % - 23.49 %	1.91	6,109	yes
	Mother's education	secondary	15.39 %	13.98 % - 16.79 %	1.92	4,876	yes
	Region	baringo	19.48 %	16.60 % - 22.36 %	0.55	396	yes
	Region	bomet	23.26 %	18.67 % - 27.85 %	1.13	368	yes
	Region	bungoma	18.54 %	13.55 % - 23.52 %	1.66	387	yes
	Region	busia	16.00 %	11.65 % - 20.35 %	1.37	374	yes
	Region	elgeyo-marakwet	21.49 %	16.25 % - 26.72 %	1.54	363	yes
	Region	embu	19.30 %	12.36 % - 26.25 %	1.86	231	yes
	Region	garissa	9.49 %	7.38 % - 11.59 %	0.68	507	yes
	Region	homa bay	11.37 %	7.73 % - 15.01 %	1.27	370	yes
	Region	isiolo	12.98 %	7.48 % - 18.49 %	2.95	422	yes
	Region	kajiado	14.70 %	9.38 % - 20.02 %	2.15	366	yes
	Region	kakamega	11.76 %	8.40 % - 15.11 %	0.97	345	yes
	Region	kericho	19.27 %	14.46 % - 24.07 %	1.39	360	yes
	Region	kiambu	14.75 %	9.49 % - 20.01 %	1.67	291	yes

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Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Region	kilifi	37.39 %	31.35 % - 43.42 %	1.41	347	yes
	Region	kirinyaga	11.46 %	7.30 % - 15.61 %	1.04	235	yes
	Region	kisii	16.93 %	12.78 % - 21.09 %	0.93	290	yes
	Region	kisumu	8.88 %	5.10 % - 12.65 %	1.76	385	yes
	Region	kitui	22.92 %	17.08 % - 28.75 %	1.51	300	yes
	Region	kwale	22.19 %	15.41 % - 28.98 %	2.65	382	yes
	Region	laikipia	11.93 %	8.65 % - 15.21 %	0.67	252	yes
	Region	lamu	15.22 %	10.46 % - 19.99 %	1.73	378	yes
	Region	machakos	13.93 %	9.11 % - 18.75 %	1.23	245	yes
	Region	makueni	20.71 %	15.73 % - 25.69 %	1.12	284	yes
	Region	mandera	20.01 %	16.48 % - 23.55 %	1.65	812	yes
	Region	marsabit	19.71 %	14.30 % - 25.11 %	2.32	482	yes
	Region	meru	25.70 %	18.39 % - 33.00 %	1.88	258	yes
	Region	migori	14.10 %	10.33 % - 17.86 %	1.33	437	yes
	Region	mombasa	12.99 %	9.17 % - 16.81 %	1.02	303	yes
	Region	murang'a	8.14 %	4.60 % - 11.68 %	1.01	232	yes
	Region	nairobi	11.85 %	8.44 % - 15.25 %	1.04	360	yes
	Region	nakuru	18.96 %	14.88 % - 23.03 %	1.11	394	yes
	Region	nandi	15.66 %	10.18 % - 21.13 %	1.97	333	yes
	Region	narok	20.19 %	15.80 % - 24.58 %	1.58	508	yes
	Region	nyamira	14.94 %	9.12 % - 20.76 %	1.61	232	yes
	Region	nyandarua	18.64 %	12.58 % - 24.71 %	1.66	263	yes
	Region	nyeri	12.22 %	6.64 % - 17.80 %	1.50	199	yes
	Region	samburu	30.30 %	25.38 % - 35.21 %	1.53	512	yes
	Region	siaya	20.38 %	15.27 % - 25.50 %	1.46	348	yes
	Region	taita taveta	16.50 %	11.81 % - 21.20 %	0.96	231	yes
	Region	tana river	19.89 %	15.64 % - 24.14 %	1.70	577	yes
	Region	tharaka-nithi	19.50 %	13.65 % - 25.36 %	1.31	231	yes
	Region	trans nzoia	20.33 %	14.02 % - 26.63 %	2.07	323	yes
	Region	turkana	21.98 %	16.95 % - 27.02 %	1.96	509	yes
	Region	uasin gishu	13.69 %	9.63 % - 17.75 %	1.23	340	yes
	Region	vihiga	15.82 %	10.98 % - 20.67 %	1.29	281	yes
	Region	wajir	12.25 %	9.72 % - 14.78 %	0.89	574	yes
	Region	west pokot	33.81 %	29.34 % - 38.27 %	1.65	710	yes
	Sex of child	female	15.06 %	14.01 % - 16.11 %	1.92	8,531	yes
	Sex of child	male	19.65 %	18.43 % - 20.87 %	2.16	8,796	yes
Survival to age five	National	all	0.83 %	0.77 % - 0.89 %	2.17	183,527	yes
	Residence	rural	0.83 %	0.77 % - 0.90 %	1.63	122,488	yes
	Residence	urban	0.81 %	0.69 % - 0.94 %	3.01	61,039	yes
	Wealth quintile	1	0.88 %	0.77 % - 0.99 %	2.33	62,117	yes
	Wealth quintile	2	0.86 %	0.73 % - 0.98 %	1.48	32,343	yes
	Wealth quintile	3	0.78 %	0.65 % - 0.90 %	1.66	31,894	yes
	Wealth quintile	4	0.86 %	0.71 % - 1.02 %	2.42	33,087	yes
	Wealth quintile	5	0.75 %	0.58 % - 0.92 %	2.35	24,086	yes
	Mother's education	higher	0.65 %	0.49 % - 0.82 %	2.22	21,314	yes
	Mother's education	none	0.79 %	0.65 % - 0.93 %	2.92	46,610	yes
	Mother's education	primary	0.90 %	0.81 % - 0.99 %	1.65	72,215	yes
	Mother's education	secondary	0.82 %	0.69 % - 0.95 %	2.34	43,388	yes
	Region	baringo	1.09 %	0.78 % - 1.41 %	1.05	4,340	yes
	Region	bomet	0.55 %	0.33 % - 0.77 %	0.89	3,883	yes
	Region	bungoma	1.00 %	0.66 % - 1.35 %	1.33	4,304	yes
	Region	busia	0.95 %	0.65 % - 1.25 %	0.98	3,979	yes
	Region	elgeyo-marakwet	0.66 %	0.47 % - 0.86 %	0.57	3,848	yes
	Region	embu	0.89 %	0.40 % - 1.38 %	1.77	2,490	yes
	Region	garissa	0.84 %	0.46 % - 1.22 %	2.56	5,655	yes
	Region	homa bay	1.13 %	0.79 % - 1.47 %	1.06	3,920	yes
	Region	isiolo	0.60 %	0.30 % - 0.89 %	1.85	4,778	yes
	Region	kajiado	0.65 %	0.38 % - 0.92 %	1.19	4,050	yes
	Region	kakamega	0.81 %	0.54 % - 1.08 %	0.87	3,652	yes
	Region	kericho	0.56 %	0.29 % - 0.83 %	1.28	3,822	yes
	Region	kiambu	0.75 %	0.40 % - 1.10 %	1.35	3,097	yes
	Region	kilifi	0.75 %	0.35 % - 1.15 %	2.15	3,942	yes
	Region	kirinyaga	1.12 %	0.58 % - 1.66 %	1.66	2,404	yes
	Region	kisii	0.73 %	0.43 % - 1.04 %	1.01	3,055	yes
	Region	kisumu	0.84 %	0.57 % - 1.10 %	0.88	3,939	yes
	Region	kitui	0.50 %	0.25 % - 0.74 %	0.98	3,040	yes

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Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Region	kwale	0.56 %	0.28 % - 0.85 %	1.53	4,036	yes
	Region	laikipia	0.96 %	0.49 % - 1.43 %	1.71	2,826	yes
	Region	lamu	0.98 %	0.65 % - 1.31 %	1.15	3,912	yes
	Region	machakos	0.80 %	0.40 % - 1.20 %	1.37	2,646	yes
	Region	makueni	0.74 %	0.31 % - 1.17 %	1.78	2,693	yes
	Region	mandera	0.43 %	0.20 % - 0.66 %	2.66	8,269	yes
	Region	marsabit	0.30 %	0.16 % - 0.43 %	0.79	4,767	yes
	Region	meru	0.63 %	0.29 % - 0.97 %	1.31	2,712	yes
	Region	migori	1.46 %	1.02 % - 1.90 %	1.70	4,804	yes
	Region	mombasa	1.02 %	0.61 % - 1.43 %	1.43	3,322	yes
	Region	murang'a	0.92 %	0.51 % - 1.33 %	1.19	2,441	yes
	Region	nairobi	0.85 %	0.55 % - 1.16 %	1.14	4,028	yes
	Region	nakuru	1.00 %	0.68 % - 1.31 %	1.03	3,876	yes
	Region	nandi	0.68 %	0.33 % - 1.03 %	1.59	3,387	yes
	Region	narok	0.51 %	0.22 % - 0.81 %	2.20	5,064	yes
	Region	nyamira	0.84 %	0.46 % - 1.22 %	1.18	2,626	yes
	Region	nyandarua	0.89 %	0.53 % - 1.25 %	1.02	2,688	yes
	Region	nyeri	1.06 %	0.60 % - 1.51 %	1.04	2,036	yes
	Region	samburu	0.74 %	0.41 % - 1.07 %	2.06	5,236	yes
	Region	siaya	1.20 %	0.79 % - 1.62 %	1.36	3,618	yes
	Region	taita taveta	0.54 %	0.24 % - 0.84 %	1.06	2,446	yes
	Region	tana river	0.85 %	0.54 % - 1.16 %	1.69	5,733	yes
	Region	tharaka-nithi	0.50 %	0.20 % - 0.80 %	1.06	2,281	yes
	Region	trans nzoia	0.81 %	0.55 % - 1.07 %	0.83	3,807	yes
	Region	turkana	1.01 %	0.65 % - 1.37 %	1.95	5,721	yes
	Region	uasin gishu	0.69 %	0.42 % - 0.97 %	1.00	3,482	yes
	Region	vihiga	0.87 %	0.54 % - 1.20 %	1.01	3,033	yes
	Region	wajir	1.13 %	0.89 % - 1.36 %	0.90	6,921	yes
	Region	west pokot	0.87 %	0.56 % - 1.17 %	1.95	6,918	yes
	Sex of child	female	0.73 %	0.65 % - 0.81 %	1.93	90,474	yes
	Sex of child	male	0.92 %	0.83 % - 1.01 %	2.26	93,053	yes
Wasting, weight-for-height below -2 SD	National	all	4.91 %	4.46 % - 5.36 %	1.97	17,332	yes
	Residence	rural	5.41 %	4.88 % - 5.94 %	1.68	11,659	yes
	Residence	urban	3.99 %	3.18 % - 4.79 %	2.50	5,673	yes
	Wealth quintile	1	9.49 %	8.45 % - 10.54 %	1.95	5,849	yes
	Wealth quintile	2	3.12 %	2.41 % - 3.84 %	1.33	3,028	yes
	Wealth quintile	3	4.33 %	3.41 % - 5.24 %	1.59	3,020	yes
	Wealth quintile	4	4.08 %	3.08 % - 5.08 %	2.10	3,155	yes
	Wealth quintile	5	2.61 %	1.71 % - 3.50 %	1.87	2,280	yes
	Mother's education	higher	3.03 %	2.07 % - 4.00 %	1.90	2,324	yes
	Mother's education	none	15.44 %	13.66 % - 17.22 %	2.54	4,020	yes
	Mother's education	primary	4.42 %	3.74 % - 5.09 %	1.70	6,118	yes
	Mother's education	secondary	3.16 %	2.56 % - 3.77 %	1.51	4,870	yes
	Region	baringo	12.82 %	6.50 % - 19.14 %	3.71	398	yes
	Region	bomet	3.56 %	1.67 % - 5.44 %	1.00	369	yes
	Region	bungoma	1.74 %	0.05 % - 3.44 %	1.69	386	yes
	Region	busia	2.91 %	1.11 % - 4.71 %	1.11	374	yes
	Region	elgeyo-marakwet	5.41 %	1.77 % - 9.05 %	2.45	364	yes
	Region	embu	5.30 %	2.36 % - 8.25 %	1.03	230	yes
	Region	garissa	15.22 %	10.30 % - 20.13 %	2.48	509	yes
	Region	homa bay	1.44 %	0.12 % - 2.75 %	1.17	369	yes
	Region	isiolo	6.69 %	3.00 % - 10.37 %	2.39	422	yes
	Region	kajiado	7.11 %	4.09 % - 10.12 %	1.32	368	yes
	Region	kakamega	1.77 %	0.33 % - 3.21 %	1.07	345	yes
	Region	kericho	2.36 %	0.29 % - 4.42 %	1.74	360	yes
	Region	kiambu	3.12 %	1.06 % - 5.19 %	1.07	291	yes
	Region	kilifi	7.49 %	4.40 % - 10.58 %	1.24	346	yes
	Region	kirinyaga	2.37 %	0.47 % - 4.28 %	0.96	235	yes
	Region	kisii	3.61 %	1.40 % - 5.82 %	1.06	290	yes
	Region	kisumu	3.15 %	1.21 % - 5.10 %	1.23	384	yes
	Region	kitui	3.93 %	1.79 % - 6.08 %	0.95	300	yes
	Region	kwale	5.85 %	3.60 % - 8.11 %	0.92	383	yes
	Region	laikipia	2.82 %	0.72 % - 4.91 %	1.05	252	yes
	Region	lamu	3.54 %	1.70 % - 5.39 %	0.99	380	yes

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Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Region	machakos	3.22 %	0.98 % - 5.46 %	1.03	244	yes
	Region	makueni	3.64 %	1.43 % - 5.84 %	1.03	285	yes
	Region	mandera	17.05 %	13.65 % - 20.45 %	1.71	806	yes
	Region	marsabit	20.68 %	14.48 % - 26.88 %	2.97	486	yes
	Region	meru	7.26 %	3.23 % - 11.29 %	1.61	256	yes
	Region	migori	2.42 %	0.69 % - 4.15 %	1.44	436	yes
	Region	mombasa	4.93 %	2.32 % - 7.54 %	1.15	303	yes
	Region	murang'a	1.52 %	-0.02 % - 3.06 %	0.96	232	yes
	Region	nairobi	2.71 %	0.91 % - 4.52 %	1.16	360	yes
	Region	nakuru	3.37 %	1.71 % - 5.03 %	0.86	392	yes
	Region	nandi	3.39 %	1.21 % - 5.57 %	1.26	333	yes
	Region	narok	2.32 %	0.64 % - 4.00 %	1.66	510	yes
	Region	nyamira	1.02 %	-0.19 % - 2.23 %	0.87	231	yes
	Region	nyandarua	2.10 %	0.32 % - 3.88 %	1.05	262	yes
	Region	nyeri	3.11 %	-0.08 % - 6.31 %	1.76	199	yes
	Region	samburu	15.30 %	12.15 % - 18.45 %	1.02	512	yes
	Region	siaya	1.47 %	0.16 % - 2.78 %	1.08	349	yes
	Region	taita taveta	4.34 %	1.01 % - 7.67 %	1.60	230	yes
	Region	tana river	11.17 %	8.39 % - 13.95 %	1.17	576	yes
	Region	tharaka-nithi	3.70 %	1.45 % - 5.94 %	0.85	231	yes
	Region	trans nzoia	3.57 %	1.82 % - 5.33 %	0.75	323	yes
	Region	turkana	22.07 %	16.31 % - 27.82 %	2.56	510	yes
	Region	uasin gishu	3.43 %	1.48 % - 5.38 %	1.01	340	yes
	Region	vihiga	2.53 %	0.11 % - 4.96 %	1.74	281	yes
	Region	wajir	22.98 %	19.51 % - 26.45 %	1.03	581	yes
	Region	west pokot	10.49 %	7.37 % - 13.61 %	1.92	709	yes
	Sex of child	female	4.38 %	3.79 % - 4.97 %	1.84	8,522	yes
	Sex of child	male	5.42 %	4.82 % - 6.02 %	1.59	8,810	yes
Zero-dose child	National	all	2.96 %	2.31 % - 3.61 %	1.36	3,561	yes
	Residence	rural	3.26 %	2.45 % - 4.06 %	1.28	2,394	yes
	Residence	urban	2.43 %	1.33 % - 3.52 %	1.53	1,167	yes
	Wealth quintile	1	5.04 %	3.85 % - 6.23 %	0.93	1,200	yes
	Wealth quintile	2	2.18 %	1.06 % - 3.30 %	0.99	650	yes
	Wealth quintile	3	3.64 %	1.70 % - 5.59 %	1.71	610	yes
	Wealth quintile	4	3.22 %	1.31 % - 5.13 %	1.94	634	yes
	Wealth quintile	5	0.48 %	0.18 % - 0.77 %	0.22	467	yes
	Mother's education	higher	1.82 %	-0.01 % - 3.65 %	2.21	454	yes
	Mother's education	none	11.61 %	9.04 % - 14.18 %	1.32	787	yes
	Mother's education	primary	1.47 %	0.79 % - 2.15 %	1.03	1,241	yes
	Mother's education	secondary	2.58 %	1.41 % - 3.75 %	1.53	1,079	yes
	Region	baringo	2.04 %	-1.84 % - 5.92 %	1.53	78	yes
	Region	bomet	1.47 %	-1.41 % - 4.36 %	1.17	79	yes
	Region	bungoma	—	-	—	84	NO
	Region	busia	—	-	—	72	NO
	Region	elgeyo-marakwet	5.20 %	0.29 % - 10.11 %	1.04	82	yes
	Region	embu	—	-	—	44	NO
	Region	garissa	34.13 %	21.91 % - 46.35 %	1.61	93	yes
	Region	homa bay	2.52 %	-1.37 % - 6.41 %	1.14	71	yes
	Region	isiolo	3.41 %	-1.56 % - 8.38 %	1.76	90	yes
	Region	kajiado	4.93 %	0.17 % - 9.68 %	0.88	70	yes
	Region	kakamega	—	-	—	80	NO
	Region	kericho	4.80 %	-1.90 % - 11.50 %	1.94	76	yes
	Region	kiambu	0.96 %	-0.91 % - 2.83 %	0.58	60	yes
	Region	kilifi	—	-	—	65	NO
	Region	kirinyaga	—	-	—	53	NO
	Region	kisii	0.93 %	-0.91 % - 2.78 %	0.56	58	yes
	Region	kisumu	—	-	—	79	NO
	Region	kitui	9.19 %	0.61 % - 17.77 %	1.68	73	yes
	Region	kwale	6.76 %	1.64 % - 11.87 %	0.88	81	yes
	Region	laikipia	2.99 %	-1.25 % - 7.24 %	0.95	59	yes
	Region	lamu	1.87 %	-1.75 % - 5.50 %	1.56	84	yes
	Region	machakos	2.38 %	-2.27 % - 7.04 %	1.14	47	yes
	Region	makueni	4.70 %	-3.82 % - 13.23 %	2.74	65	yes
	Region	mandera	36.81 %	29.03 % - 44.58 %	1.08	159	yes
	Region	marsabit	8.00 %	1.83 % - 14.18 %	1.29	96	yes
	Region	meru	1.84 %	-1.67 % - 5.35 %	0.91	51	yes

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Indicator	Dimension	Level	Estimate	95 % CI	deff	n	Rel.
	Region	migori	0.45 %	-0.45 % - 1.35 %	0.46	98	yes
	Region	mombasa	—	-	—	56	NO
	Region	murang'a	3.41 %	-3.21 % - 10.03 %	1.42	41	yes
	Region	nairobi	2.64 %	-0.40 % - 5.67 %	0.80	86	yes
	Region	nakuru	0.92 %	-0.90 % - 2.74 %	0.83	88	yes
	Region	nandi	—	-	—	55	NO
	Region	narok	2.50 %	-0.73 % - 5.74 %	1.08	97	yes
	Region	nyamira	—	-	—	43	NO
	Region	nyandarua	—	-	—	65	NO
	Region	nyeri	—	-	—	35	NO
	Region	samburu	9.51 %	-2.97 % - 21.99 %	4.90	104	yes
	Region	siaya	0.70 %	-0.69 % - 2.10 %	0.50	70	yes
	Region	taita taveta	1.57 %	-1.45 % - 4.59 %	0.77	50	yes
	Region	tana river	7.45 %	1.80 % - 13.09 %	1.28	106	yes
	Region	tharaka-nithi	—	-	—	48	NO
	Region	trans nzoia	—	-	—	63	NO
	Region	turkana	3.49 %	-0.22 % - 7.20 %	1.32	124	yes
	Region	uasin gishu	1.48 %	-1.41 % - 4.38 %	1.08	72	yes
	Region	vihiga	—	-	—	58	NO
	Region	wajir	6.95 %	2.06 % - 11.84 %	1.06	110	yes
	Region	west pokot	3.02 %	0.33 % - 5.70 %	0.92	143	yes
	Sex of child	female	2.76 %	2.00 % - 3.53 %	0.99	1,742	yes
	Sex of child	male	3.15 %	2.14 % - 4.16 %	1.58	1,819	yes

Notes: Source: Kenya 2022 DHS (KE2022DHS), committed run.

K.3 What these tables will not support

- **A comparison between the two surveys read as a comparison between the two countries' health systems.** The questionnaires and recodes differ, and Appendix B shows how much.
- **A district figure.** These are national, residence, region and sub-region estimates. Below that level the design does not support a direct estimate, and the small-area chapter is the route, with its shrinkage weights published.
- **A trend.** Each table is one round. The projection chapter labels its three products — interpolation, nowcast and forecast — and the labels are the point.
- **A causal statement.** Nothing in these tables is an effect. Every cell is a prevalence, a rate or a mean in a stated population.

Appendix L. The estate, module by module

Every Julia module in the estate, by layer, with its line count. 48 modules and 4,789 lines in the system layers, plus -19 modules in the survey estimation core. This is the map Laboratory 01 asks you to draw.

L.1 Models — 14 modules, 1,329 lines

The health-system and per-card population-health models.

Table 304: Models — 14 modules, 1,329 lines

Module	Lines
`DiseaseBurden.jl`	400
`HealthFinancing.jl`	236
`WorkforcePlanning.jl`	190
`FacilityCapacity.jl`	122
`Population.jl`	117
`SupplyChainModel.jl`	108
`Reference.jl`	90
`Epidemiology.jl`	18
`Supply.jl`	13
`Demand.jl`	10
`Financing.jl`	9
`Outcomes.jl`	8
`Workforce.jl`	5
`Demography.jl`	3

L.2 Core — 6 modules, 651 lines

Configuration, types, schema, validation, scenarios.

Table 305: Core — 6 modules, 651 lines

Module	Lines
`Config.jl`	187
`Validation.jl`	161
`DataSchema.jl`	132
`HealthTypes.jl`	87
`ScenarioManager.jl`	49
`Types.jl`	35

L.3 Optimization — 10 modules, 601 lines

Mathematical programmes, solved with HiGHS.

Table 306: Optimization — 10 modules, 601 lines

Module	Lines
`FacilityPlanning.jl`	189
`CostBenefit.jl`	148
`ReferralOptimization.jl`	66
`WorkforceOptimization.jl`	62
`SupplyDistribution.jl`	61
`FacilityLocation.jl`	18
`SupplyChain.jl`	17
`WorkforceAllocation.jl`	16
`BudgetAllocation.jl`	13
`ReferralNetwork.jl`	11

L.4 GIS — 2 modules, 597 lines

Geographic accessibility and climate risk.

Table 307: GIS — 2 modules, 597 lines

Module	Lines
`Accessibility.jl`	443
`ClimateRisk.jl`	154

L.5 Simulation — 3 modules, 488 lines

The run engines.

Table 308: Simulation — 3 modules, 488 lines

Module	Lines
`DynamicEngine.jl`	296
`HealthEngine.jl`	151
`Engine.jl`	41

L.6 Integration — 4 modules, 425 lines

Poverty, macro, CGE and education links.

Table 309: Integration — 4 modules, 425 lines

Module	Lines
`Poverty.jl`	136
`MacroLink.jl`	135
`CDCGELink.jl`	94
`EducationLink.jl`	60

L.7 API — 2 modules, 217 lines

REST routes and the application.

Table 310: API — 2 modules, 217 lines

Module	Lines
`Routes.jl`	197
`app.jl`	20

L.8 Data — 3 modules, 204 lines

Loaders and persistence.

Table 311: Data — 3 modules, 204 lines

Module	Lines
`Database.jl`	97
`HealthLoader.jl`	80
`Loader.jl`	27

L.9 Results — 2 modules, 166 lines

Indicators, exports and reports.

Table 312: Results — 2 modules, 166 lines

Module	Lines
`Reports.jl`	95
`Indicators.jl`	71

L.10 Services — 2 modules, 111 lines

The job service and the scenario store.

Table 313: Services — 2 modules, 111 lines

Module	Lines
`JobService.jl`	73
`ScenarioStore.jl`	38

L.11 The survey estimation core

29 modules and 8,267 lines implementing design-based estimation for the population-health layer, with 24 optional R scripts as a second implementation and 97 model configurations.

Table 314: The survey estimation core

Module	Lines
`Harmonisation.jl`	783
`Models.jl`	643
`CrossSectorExports.jl`	577
`ModelCatalogue.jl`	499
`Causal.jl`	404
`Validation.jl`	381

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Module	Lines
`Microsimulation.jl`	365
`Inequality.jl`	336
`Prediction.jl`	320
`GISAccessibility.jl`	306
`FeatureEngineering.jl`	279
`HealthSystemPlanning.jl`	253
`ModelRegistry.jl`	245
`Config.jl`	236
`SurveyDesign.jl`	233
`Multilevel.jl`	227
`MissingData.jl`	220
`Optimisation.jl`	218
`Explainability.jl`	210
`Forecasting.jl`	202
`Reporting.jl`	199
`DescriptiveAnalytics.jl`	190
`DataInventory.jl`	189
`SpatialModels.jl`	184
`CLI.jl`	176
EDISDHSHealth.jl	144
`LatentIndex.jl`	134
`SmallAreaEstimation.jl`	60
`DHSIngestion.jl`	54

L.12 Cohort construction, step by step

Before any estimator runs, a cohort is built: a file is opened, a universe is applied, exclusions are taken in order, and what survives is the denominator. Every exclusion below is a decision that changes the estimate, and every one of them is recorded rather than implicit.

Table 315: 35 construction steps across 12 cohorts

Cohort	Step	Remaining
anaemia child	children in KR	15,522
	aged 6-59 months (eligible for testing)	4,030
	haemoglobin measured	3,944
anc4	births in KR	15,522
	ANC visits recorded (98/99 excluded)	10,219
children ever born	women in IR	18,506
	valid age 15-49 with CEB recorded	18,506
facility delivery	births in KR	15,522
	place of delivery recorded	15,522
fever 2w	children in KR	15,522
	living children 0-59 months	4,530
	fever reported (8/9 excluded)	4,527
malaria rdt	household members in PR	91,167
	children under 5	16,362
	valid test result (undetermined excluded)	4,796
maternal cascade	births in KR	15,522
	ANC and place of delivery both recorded	10,219
modern contraception	women in IR	18,506
	contraceptive use recorded	18,506
	currently married / in union	11,379
stunting	children in KR	15,522

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Cohort	Step	Remaining
	living children	14,710
	aged 0-59 months	4,530
	valid z-score (flags 9996-9999 and |z|>6 excluded)	4,423
under5 survival	births in BR	57,906
	valid birth/interview dates	57,906
	born within 10-year window	30,155
	child-age intervals generated	143,471
wasting	children in KR	15,522
	living children	14,710
	aged 0-59 months	4,530
	valid z-score (flags 9996-9999 and |z|>6 excluded)	4,413
zero dose	children in KR	15,522
	living children	14,710
	aged 12-23 months (standard denominator)	953

Two readings are worth making explicit. A cohort that loses a large share at one step has a denominator question attached to it, and the step names which. And a cohort whose final n is a few thousand cannot support a district table, whatever the national sample size suggests.