

THE LANCET

Infectious Diseases

Supplementary appendix

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Supplement to: IHME Pathogen Core Group. Global burden associated with
85 pathogens in 2019: a systematic analysis for the Global Burden of Disease Study
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1 Appendix: supplementary methods and results to “Global burden
2 associated with 85 pathogens in 2019: a systematic analysis for the
3 Global Burden of Disease Study 2019”

4 This appendix provides further methodological details and supplementary figures/tables for “*Global burden associated*
5 *with 85 pathogens in 2019: a systematic analysis for the Global Burden of Disease Study 2019*”. Parts of the appendix are
6 taken directly from the appendix of the papers “*Global burden of bacterial antimicrobial resistance in 2019: a systematic*
7 *analysis*”¹ and “*The burden of antimicrobial resistance in the Americas in 2019: a cross-country systematic analysis*”²
8 which are referenced throughout the text.

9

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41 **Section 1: List of Abbreviations**

42	Abbreviation	Full phrase
43	DALYs	disability-adjusted life-years
44	GBD	Global Burden of Disease
45	CODEm	Cause of Death Ensemble model
46	GATHER	Guidelines for Accurate and Transparent Health Estimates Reporting
47	GHDx	Global Health Data Exchange
48	HIV	human immunodeficiency virus
49	HPV	human papillomavirus
50	ICD	International Classification of Diseases
51	LMICs	low- and middle-income countries
52	MEPCO	multinomial estimation with partial and composite observations
53	NTDs	neglected tropical diseases
54	RSV	respiratory syncytial virus
55	ST-GPR	Spatiotemporal gaussian process regression
56	UI	uncertainty interval
57	YLDs	years lived with disability
58	YLLs	years of life lost

59 **Section 2: Data sources^{1,2}**

60 We use a subset of the input data described in the GB-AMR capstone paper.¹ This subset has information on
61 underlying cause or primary diagnosis at admission or sample specimen type to determine the infectious syndrome
62 which have a positive culture of pathogen and did not have a sampling framework that would bias the aetiology
63 estimation towards a specific pathogen (ie, did not deliberately sample until 100 cases of every pathogen of interest
64 had been obtained).

65 The input data source types that met these criteria were:

66 **Section 2.1: Multiple causes of death and vital registration (MCoD-VR) data.**

67 These are certificates from vital records provide the underlying, immediate and intermediate causes and conditions
68 contributing to deaths observed in the following national health systems:

- 69 • United States National Vital Statistics System
- 70 • Brazil Mortality Information System
- 71 • National Institute of Statistics (Italy)
- 72 • Statistics South Africa
- 73 • National Institute of Statistics and Geography (Mexico)
- 74 • National Administrative Department of Statistics (Colombia)
- 75 • Taiwan Ministry of Health and Welfare

76 **Section 2.2: Hospital discharge data.**

77 Hospital admissions and discharge data, which include primary and secondary diagnosis for each patient.

78 • USA National Hospital Discharge Survey

79 • USA State Inpatient Databases

80 • Brazil Hospital Information System

81 • Italy Hospital Inpatient Discharges

82 • Sistema Automatizado de Egresos Hospitalarios (Mexico)

83 • Austria Hospital Inpatient Discharges

84 • New Zealand National Minimum Dataset

85 • Canada Discharge Abstract Database

86 **Section 2.3: Linkage data sources.**

87 For two of the hospital discharge sources mentioned above, namely Italy Friuli-Venezia Giulia and New Zealand

88 National Minimum dataset, we have linked admission records to microbial positive cultures, which are referred as

89 linkage data throughout the paper.

90 **Section 2.4: Mortality surveillance in the Child Health and Mortality Prevention Surveillance (CHAMPS) study.**

91 It comprises under-5 mortality surveillance in South Africa, Mali, Bangladesh, Kenya, Ethiopia, and Mozambique.
92 This study provides information about pathogens contributing to death by collecting a minimally invasive tissue
93 sampling (MITS) in addition to vital records. MITS is also known as a pathology-based autopsy which improves the
94 understanding of mortality surveillance specially in low and middle income settings.

95 **Section 2.5: Literature review of the microbial aetiology of meningitis, maternal and neonatal sepsis, lower respiratory infections, urinary tract infections, skin infections, peritonitis, and bone and joint infections**

96 Search strings were used in PubMed to look systematically for the causative microorganisms of the following
97 infectious syndromes:

98 *Section 2.5.1: Meningitis*

99 ((meningitis[title]) AND (1990/05/01[PDat] : 2018/12/31[PDat]) AND ((etiolog*[title/abstract]) AND
100 Humans[MeSH Terms]))

101

102 *Section 2.5.2: Maternal and neonatal sepsis and LRI aetiology*

103 Aetiology terms, combined with OR:

- 104 • Infection (Infect*)
- 105 • Microbiology (Microbiolog*)
- 106 • Aetiology (Aetiolog*)
- 107 • Etiology (Etiolog*)
- 108 • Virology (Virolog*)
- 109 • Bacteriology (Bacteriolog*)
- 110 • Fungus (fung*)

111 AND

112 Syndrome terms, combined with OR:

113 Maternal Sepsis

- 114 • puerperal sepsis (puerper* sepsis)

- 117 • maternal sepsis (matern* sepsis)
118 • puerperal septicaemia (puerper* septicaemia, American spelling too - septicemia)
119 • maternal septicaemia (matern* septicaemia, American spelling too - septicemia)
120 • puerperal infection (puerper* infection)
121 • maternal infection (matern* infection)
122 • puerperal bacteraemia (puerper* bacteraemia, American spelling too - bacteremia)
123 • maternal bacteraemia (matern* bacteraemia, American spelling too - bacteremia)

124 Neonatal Sepsis

- 125 • Neonatal sepsis (Neonat* sepsis within 3 or 5 words of each other)
126 • Neonatal septicaemia (Neonat* septicaemia within 3 or 5 words of each other, American spelling too - septicemia)
127
128 • Infant sepsis (Infant* sepsis)
129 • Infant septicaemia (Infant* septicaemia, American spelling too - septicemia)
130 • Neonatal bacteraemia (Neonat* bacteraemia, American spelling too - bacteremia)
131 • Infant bacteraemia (Infant* bacteraemia, American spelling too - bacteremia)

132 Lower respiratory infections

- 133 • LRI
134 • Lower respiratory infection
135 • LRTI
136 • Lower respiratory tract infection
137 • Pneumonia

138 *Section 2.5.3: Urinary tract infections aetiology*

139 ("complicated"[Title/Abstract] OR "uncomplicated"[Title/Abstract]) AND (("Cystitis/etiology"[majr:noexp] OR
140 "Cystitis/microbiology"[majr:noexp] OR ("Pyelonephritis/etiology"[marj:noexp] OR
141 "Pyelonephritis/microbiology"[majr:noexp]) OR ("Urinary Tract Infections/etiology"[majr:noexp] OR "Urinary
142 Tract Infections/microbiology"[majr:noexp])) OR ("Urinary tract infections"[tiab] AND ("etiology"[tiab] OR
143 "microbiology"[tiab]))

144 (("urinary tract infection*"[title]) AND (1990/05/01[PDat] : 2018/12/31[PDat]) AND ((etilog*[title/abstract] OR
145 "Urinary Tract Infections/microbiology"[Mesh]) AND Humans[MeSH Terms]) NOT Review[ptyp]

146 *Section 2.5.4: Skin infections aetiology*

147 (("Cellulitis/epidemiology"[majr:noexp] OR "Cellulitis/etiology"[majr:noexp] OR
148 "Cellulitis/microbiology"[majr:noexp]) OR ("Pyoderma/epidemiology"[majr:noexp] OR
149 "Pyoderma/etiology"[marj:noexp] OR "Pyoderma/microbiology"[majr:noexp]) OR

150 "Pressure Ulcer/microbiology"[majr:noexp])

151 ("skin and soft tissue infection"[title] OR cellulitis[title] OR erysipelas[title]) AND (1990/05/01[PDat] :
152 2018/12/31[PDat]) AND (etilog*[title/abstract] OR "Cellulitis/microbiology"[Mesh]) AND Humans[MeSH Terms]
153 NOT Review[ptyp]

154 *Section 2.5.5: Intra-abdominal infection aetiology*

155 (("Peritonitis/epidemiology"[majr:noexp] OR "Peritonitis /etiology"[majr:noexp] OR "Peritonitis
156 /microbiology"[majr:noexp]) OR ("Intraabdominal infections/epidemiology"[majr:noexp] OR "Intraabdominal
157 infections /etiology"[marj:noexp] OR "Intraabdominal infections /microbiology"[majr:noexp]) OR ("abdominal
158 abscess/epidemiology"[majr:noexp] OR " abdominal abscess /etiology"[majr:noexp] OR "abdominal
159 abscess/microbiology"[majr:noexp]))

160 *Section 2.5.6: Bone and joint infections aetiology*

161 ("Osteomyelitis/etiology"[majr:noexp] OR "Osteomyelitis/microbiology"[majr:noexp] NOT 'chronic') OR
162 ("Arthritis, infectious/etiology"[marj:noexp] OR "Arthritis, infectious/microbiology"[majr:noexp] NOT 'lyme')

163 **Section 2.6: Exclusion criteria for literature reviews**

164 Studies were excluded from full text review if:

- 165 • The study did not include at least one of the following: *E.coli*, *K.pneumoniae*, *S.pneumoniae*, *S.aureus* or
166 *S.typhi/paratyphi*
- 167 • The entire study was conducted before 1990
- 168 • Samples were collected before 1990
- 169 • Did not perform resistance testing
- 170 • Sample is non-representative (lab strains, only resistant strains)
- 171 • Included non-human samples
- 172 • Article type was a case study
- 173 • Article type was a commentary, editorial or review with no primary data
- 174 • Isolates were not from blood culture
- 175 • There were duplicated isolates
- 176 • Travellers/non-endemic country/ no location information
- 177 • Study did not test susceptibility to antimicrobials
- 178 • There were fewer than 10 consecutive isolates used for susceptibility testing
- 179 • Could not locate the full text
- 180 • The study was uninterpretable due to poor data quality
- 181 • Studies where data was aggregated with other pathogens
- 182 • Studies using non-sterile site/mixed isolates
- 183 • Studies with no iNTS AST data

184 **Section 2.7: Laboratory-based passive surveillance data.**

185 Laboratories based in hospitals or part of public and private laboratory networks have provided information on
186 patient's specimens with positive pathogen growth. We infer the infectious syndrome from admission diagnosis if
187 this is present in data. If the former is not present, we use the type of specimen to infer the infectious syndrome of
188 the patient. Some datasets include discharge disposition of the patient and whether the infection was identified after
189 48 hrs. from admission, which allow us to classify into community- or hospital-onset infections.

190 *Section 2.7.1: Laboratory-based data with outcome:*

- 191 • **USA Becton, Dickinson, and Co. (BD) Insights, Research and Analytics Database microbiology test and in-patient hospital data:** data procured by BD via MedMined. Covers a range of regions in the United States from 2011 to 2017.
- 192 • **International Nosocomial Infection Control Consortium (INICC) surveillance online system:** data from the INICC data collection software. ICU patient microbiology and hospital data from 50 countries across Latin America, Asia, the Middle East, eastern Europe, and Africa from 2009 to 2020.
- 193 • **St. George's Hospital, University of London - Global Antimicrobial Resistance, Prescribing and Efficacy among Neonates and Children (SGUL-GARPEC) Project bloodstream infection data:** Penta-sponsored global surveillance network focusing on neonatal and paediatric antimicrobial resistance and the organisms causing blood stream infections.
- 194 • **Burden of Antibiotic Resistance in Neonates from Developing Societies (BARNARDS):** BARNARDS includes locations in Nigeria, South Africa, Pakistan, Rwanda, Bangladesh, Ethiopia and India from 2015 to 2018.
- 195 • **Lima, Peru Cayetano Heredia University (UPCH) antimicrobial resistance data:** data from UPCH hospital sites across Lima, Peru with discharge disposition for infectious pulmonary disease

196 *Section 2.7.2: Laboratory-based data without outcome:*

- **SENTRY:** SENTRY Antimicrobial Surveillance Program established by JMI Labs in 1997. Sites are in the USA, Europe, Latin America, parts of Asia, and the Western Pacific
- **Pfizer ATLAS Programme:** the Antimicrobial Testing Leadership and Surveillance (ATLAS) database includes the Tigecycline Evaluation Surveillance Trial (TEST), the Assessing Worldwide Antimicrobial Resistance Evaluation (AWARE) and the International Network for Optimal Resistance Monitoring (INFORM) programs. The study spans in coverage across more than 70 countries between 2004 and 2017.
- **WHO Meningitis surveillance:** sentinel hospital surveillance of suspected meningitis cases among children under 5 years old and positive cultures, provided by the World Health Organisation (WHO) Global Rotavirus, Invasive Bacterial Vaccine Preventable Diseases Surveillance Network Collaboration from 2008 to 2020.
- **NARMS:** The National Antimicrobial Resistance Monitoring System for Enteric Bacteria (NARMS) is a collaboration of agencies within The U.S. Department of Health and Human Services (HHS) (FDA and CDC) and the U.S. Department of Agriculture (USDA). It tracks enteric bacteria and selected animal pathogens and their resistance to antimicrobials, and data is available from 1997 onwards.
- **United States Active Bacterial Core Surveillance (ABCs) Reports:** case reports on healthcare-associated Infections and community interface infections from the Emerging Infections Program (EIP) Network coordinated by the Center for Disease Control and Prevention (CDC).
- **World Health Organization (WHO) Global Tuberculosis Programme**
- **GLASS:** Global Antimicrobial Resistance Surveillance System by WHO
- **Hospital Civil de Guadalajara Fray Antonio Alcalde, Mexico**
- **Canadian Antimicrobial Resistance Surveillance System**
- **SOAR:** Survey on Antibiotic Resistance (SOAR) sponsored by GSK.
- **ReLAVRA and SIREVA:** The Latin American Network for Antimicrobial Resistance Surveillance (ReLAVRA by its Spanish acronym) and the Serotype and Antimicrobial Resistance Surveillance Program (SIREVA by its English acronym) which are coordinated by the Pan-American Health Organization (WHO/PAHO)
- **SMART:** Study for Monitoring Antimicrobial Resistance Trends which monitors complicated intra-abdominal infections (cIAIs), complicated urinary tract infections (cUTIs) and respiratory infections worldwide, funded by Merck & Co.

239 **Section 3: Supplementary methods: a summary of the estimation process^{1,2}**

240 **Section 3.1: GBD 2019 framework**

241 The study relies on Global Burden of Disease (GBD) 2019 fatal and non-fatal estimates, and a comprehensive
 242 description of data sources, data quality, statistical modelling and analyses for GBD 2019 have been reported
 243 elsewhere.³ A brief summary of the fatal and non-fatal estimation, including a flow chart of the processes, can be
 244 found in the appendix of Murray et al. (2022).¹

245 **Section 3.2: Deaths where infection plays a role and infectious syndrome estimation**

246 *Section 3.2.1: Input data*

247 Multiple causes of death (MCoD) data are individual-based records that provide underlying causes of death and two
 248 or more intermediate causes in the chain of death. Additionally, each record includes age, sex, residence, and the
 249 date of death.

250 Hospital record with multiple diagnoses and discharge status of death represents an individual-based hospital record
 251 of a patient that provides the main diagnosis and two or more additional diagnoses. Additionally, each record
 252 includes age, sex, residence, date of admission, date of discharge, and outcome (dead or alive). Only hospital
 253 discharges with discharge status of death were used in this component model, since we aimed to estimate the
 254 fraction of deaths that involve infection and the infectious syndrome distribution of those deaths.

255 Linkage data are generated using probabilistic methods in a defined population that link individual-based hospital
 256 data to individual-based MCoD data. Linkage data offer a wider dataset that includes main diagnosis, other
 257 diagnoses, underlying cause of death, and intermediate causes of death in the chain.

258 *Section 3.2.2: Data processing and mapping*
259 Within the WHO European region, data for Italy has been extracted at the subnational level by GBD 2019 age
260 groups, sex, year, and causes of death and/or diagnoses, while data for the remaining countries have been analysed
261 at the national level. This allowed us to expand the location-years of data that we had for each Socio-demographic
262 Index (SDI)⁴ value.

263 Prepared data were mapped to GBD causes. The GBD cause list is a mutually exclusive and collectively exhaustive
264 list of diseases and injuries. The GBD cause list is organised hierarchically to accommodate different purposes and
265 needs of various users. The first two levels aggregate causes into general groupings. At Level 1, there are three
266 cause groups: communicable, maternal, neonatal, and nutritional diseases (Group 1 diseases); non-communicable
267 diseases (Group 2); and injuries (Group 3). These Level 1 aggregates are subdivided at Level 2 of the hierarchy into
268 22 cause groupings (eg, neonatal disorders, neurological disorders, and transport injuries). The disaggregation into
269 Levels 3 and 4 contains the finest level of detail for causes captured in GBD 2019. See section 14, table S1 for the
270 full GBD cause hierarchy by level.

271 The underlying cause of death or main diagnosis for each record in the data was mapped to a GBD cause. After the
272 mapping of underlying cause, we used the GBD 2019 garbage code redistribution algorithm (see appendix 1, section
273 2.4 in Vos et al.³) to ensure that all deaths had a plausible and specific underlying cause of death. The redistribution
274 of garbage codes for underlying causes of death followed the same age and sex restrictions as GBD 2019. We did
275 not redistribute garbage codes in the chain causes because the concept of a garbage code applies only to plausible
276 underlying cause of death (see Rudd et al.⁵ and appendix 1, section 2.5 in Vos et al.³).

277 *Section 3.2.3: Intermediate cause and infectious syndrome mapping hierarchy with modelling pathways*
278 Within our modelling framework, an infectious syndrome is the infection directly responsible for sepsis and serves
279 as the bridge between the underlying cause of death and sepsis. Infectious syndromes can be both underlying causes
280 of death and intermediate causes of death.

281 For mapping underlying and intermediate causes of death and hospital diagnoses to sepsis and infectious syndromes,
282 we designed a new map, called “*AMR, sepsis, and infectious syndrome map*”. This map is a list of mutually
283 exclusive and collectively exhaustive infectious syndromes that we divided into four levels to form the infectious
284 syndrome hierarchy.

285 Each level of infectious syndrome is mutually exclusive and collectively exhaustive. Furthermore, the infectious
286 syndrome hierarchy is internally consistent across any metric (eg, number, cause fraction)—aggregating across
287 Level 3 syndromes gives us Level 2 syndromes, aggregating the Level 2 syndromes gives us Level 1 syndromes,
288 and the total of Level 1 syndromes is equal to the value of sepsis (figure 4.4.2.1).

289 Level 0: All International Classification of Diseases 9th (ICD-9) or 10th revision (ICD-10) coded deaths divided into
290 three groups: explicit sepsis (any death with the specific ICD code for sepsis in the MCoD chain or hospital
291 diagnoses), implicit sepsis (any death with an infectious disease code in the underlying cause or cause chain, as well
292 as with a specific organ dysfunction) and non-sepsis (any death that does not meet either of the two aforementioned
293 criteria). More information can be found in the appendix of Murray et al. (2022).¹

294 Explicit sepsis (A40, R65.2 in ICD-10 and 039 in ICD-9): Any death has specific ICD code for sepsis in the MCoD
295 chain or hospital diagnoses was considered explicit sepsis.⁵

296

- Implicit sepsis: Any death that has an infectious disease code in the underlying cause or cause chain and a
297 specific organ dysfunction code was considered implicit sepsis
- Non-sepsis: Any death that does not meet either of the two above criteria (section 14, tables S2, S3)

298 Of the estimated infection-related deaths with explicit sepsis or implicit sepsis and infectious diseases, 59.4% occur
299 with communicable, maternal, neonatal, and nutritional underlying causes of death. 38.9% infection related deaths
300 occur with non-communicable disease as the underlying cause of death, and 1.7% occur with injuries as the
301 underlying cause of death.

303 Level 1: All implicit and explicit sepsis deaths were divided into 12 Level 1 infectious syndromes and an “other”
304 category. These are as follows: 1) Bacterial infections of the skin and subcutaneous systems; 2) Bloodstream
305 infections; 3) Gonorrhoea and chlamydia; 4) Diarrhoea; 5) Endocarditis and other cardiac infections; 6) Infections of
306 bones, joints and related organs; 7) Lower respiratory infections and all related infections in the thorax; 8)
307 Meningitis and other bacterial central nervous system infections; 9) Peritoneal and intra-abdominal infections; 10)
308 Tuberculosis; 11) Typhoid, paratyphoid, and invasive non-typhoidal *Salmonella*; 12) Urinary tract infection and
309 pyelonephritis; 13) Other infections

310 Level 2: Each Level 1 infectious syndrome was divided into Level 2 infectious syndromes based on the pathogen
311 type (eg, bacterial, fungal, viral) causing the infection. Examples include specified bacterial, unspecified bacterial,
312 fungal, viral, and unspecified pathogen.

313 Level 3: Each specified bacterial infectious syndrome in Level 2 was divided to Level 3 infectious syndromes by the
314 culprit bacterial pathogen. Table S3 (section 14) shows this list and bacterial hierarchy.

315 Due to our data often having multiple diagnoses associated with each record, a single case of sepsis could potentially
316 map to multiple candidate infectious syndromes. Because multiple infectious syndrome assignments pose a risk of
317 double counting, we employed an informative ranking hierarchy. The informative ranking allowed us to determine
318 the infectious syndrome that provided the most information on the culprit pathogen. The goal of this hierarchy was
319 to produce the most accurate pathogen burden estimate such that when there were multiple infectious syndromes, we
320 prioritised the syndrome with the most distinctive distribution. For example, bloodstream infections (BSIs) are
321 common infections in sepsis but there is often an earlier source of the infection such as a UTI, cellulitis, or LRI, and
322 each has a unique pathogen distribution that provides more information than the distribution of BSI. In the event that
323 a patient record reflected both BSI and LRI, we would assign the infectious syndrome based on the pathogen
324 distribution that would be the most proximal aetiological syndrome, LRI (please refer to the appendix of Murray et al.
325 (2022)¹ for more information).

326 After mapping the underlying and chain causes of death, our database went through two separate modelling
327 pathways. The first model estimated the fraction of deaths that are sepsis-related in each GBD cause; these sepsis-
328 related deaths for non-infectious GBD causes were combined with GBD deaths for infectious causes to create the
329 total envelope of all deaths where infection plays a role. The second pathway estimated each infectious syndrome as
330 a fraction of sepsis-related mortality in each GBD cause. In the last step of infectious syndrome estimation, the
331 fractions of sepsis by Level 1 infectious syndromes were squeezed to sum to one so as to not exceed the sepsis
332 mortality envelope and multiplied by the sepsis estimate in each GBD cause by country and territory, age, and sex in
333 2019.

334
335 *Section 3.2.4: First pathway – deaths where infection plays a role*
336 We used a mixed-effects binomial logistic regression to model the logit of the fraction of sepsis-related deaths by
337 GBD cause-age-sex-location, consistent with the modelling approach used by Rudd et al.⁵ Sex and Healthcare
338 Access and Quality Index (HAQ Index)³ were included as covariates and a nested random effect on underlying
339 cause of death was included. A separate model was run for each GBD 2019 age group (0–6, 7–27, 28–364 [days], 1–
340 4, 5–9, 10–14, 15–19, 20–24, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, 65–69, 70–74, 75–79, 80–
341 84, 85–89, 90–94, 95+ [years]):

$$\text{sepsis related deaths} \sim B(\text{total deaths}, \text{sepsis fraction})$$

$$\text{logit(sepsis fraction)} = \beta_0 + \beta_1 * \text{HAQ Index} + \beta_2 * \text{sex} + \pi_{\text{level 1, level 2}}$$

342 Where $\pi_{\text{level 1, level 2}}$ is a nested random effect on underlying cause of death. The nested random-effect’s structure in
343 the model on underlying cause of death allowed the prediction of sepsis fractions where data were limited by
344 borrowing information from diseases within the same group. There were 22 groups of underlying causes of death,
345 each categorised by physiological relatedness. We produced our predictions and uncertainty intervals (UIs) by
346 generating 1000 draws from the normal distribution of the fixed coefficients, separately for each GBD location, age
347 group, sex, and cause in 2019. The means of our results were used for the point estimates and the 95% UIs were
348
349

350 delineated using the 2.5th and 97.5th percentiles of the draws. Uncertainty is attributable to sample size variability
351 between data sources, data availability, and model specifications.

352 All underlying causes of death that are infectious diseases were included in the model; however, for these causes we
353 used the GBD death estimates rather than the modelled sepsis estimate, since infection inherently plays a role in
354 these deaths even if the pathway doesn't include sepsis. These causes and their associated infectious syndromes are
355 available in the appendix of Murray et al. (2022).¹ For all other causes, we calculated the number of sepsis-related
356 deaths in 2019 by multiplying our predictions of cause-, age group-, sex-, year-, and location-specific sepsis
357 fractions by GBD 2019 death estimates. Finally, we aggregated our results to arrive at regional and global sepsis-
358 related mortality in non-infectious underlying causes of death, which we combined with the GBD infectious disease
359 deaths estimates to create the mortality envelope of all deaths related to infection.

360 *Section 3.2.5: Second pathway – fraction of deaths where infection plays a role by infectious syndrome in each GBD
361 cause*

362 We used a mixed-effects binomial logistic regression to model the logit of the infectious syndrome fraction of
363 sepsis-related mortality by GBD cause. The model covariates varied by infectious syndrome, and all models
364 included HAQ Index as a covariate and most included a summary exposure value (SEV) scalar calculated for GBD
365 2019. To more accurately estimate the burden of pathogens responsible for infection, we separated infectious
366 syndromes into hospital-acquired and community-acquired for LRI+ and UTI. More details on the infectious
367 syndrome model covariates and age groups are found in the appendix of Murray et al. (2022).¹
368 The infectious syndrome models were specified as mixed-effects binomial logistic regressions, one for each
369 infectious syndrome and age group:

$$370 \quad \text{syndrome related deaths} \sim B(\text{total sepsis deaths}, \text{syndrome fraction})$$

$$371 \quad \text{logit(syndrome fraction)} = \beta_0 + \beta * X + \pi_{\text{level 1}, \text{level 2}}$$

372 where β and X are vectors of length for covariates and π is a nested random effect on underlying cause of death. The
373 granularity of the age groups estimated for each infectious syndrome was chosen based on the age pattern of the
374 infectious syndrome and the limitations of data sparsity.

375 As in the first pathway, we derived our predictions and UIs by generating 1000 draws from the normal distribution
376 of the fixed coefficients separately for each GBD location, age group, sex, and cause in 2019. We used the means of
377 our results for the point estimates and the 95% UIs were delineated using the 2.5th and 97.5th percentiles of the
378 draws.

379 We calculated the number of deaths attributable to each infectious syndrome in 2019 by multiplying our predictions
380 of cause-, age group-, sex-, year-, and location-specific infectious syndrome fractions by our sepsis-mortality
381 estimates from the first pathway. All infectious syndrome fractions were squeezed to sum to one prior to
382 multiplication in order to ensure that we did not exceed the sepsis mortality envelope.

383 Out of the 12 explicit Level 1 infectious syndromes included in our hierarchy, we excluded (i) tuberculosis (TB), (ii)
384 typhoid, paratyphoid, and invasive non-typhoidal *Salmonella*, and (iii) gonorrhoea and chlamydia from our binomial
385 mixed-effects linear regression model. Instead, we used the published results from GBD 2019⁴ for these causes of
386 death, as we believe the GBD 2019 estimates fully represent these infectious syndromes because they are usually not
387 intermediate causes of death.

388 *Section 3.2.6: Model validation*

389 Infectious syndrome modelling aims to predict which cases of infection belong to a specific infectious syndrome,
390 which is a multi-class classification problem. We therefore use the Area Under the Receiver Operating
391 Characteristics (ROC) Curve (AUC) and accuracy to evaluate model performance. More information on this can be
392 found in the appendix of Murray et al. (2022).¹
393

394 The out-of-sample strategy for this validation excluded 20% of the sample on each iteration. Table 3.2.6.1 reports
395 the Accuracy and AUC score⁶ for each of the age groups within the infectious syndrome models and table 3.2.6.2

396 reports the same metrics for the sepsis models. 99% of the models have an AUC score between 0.7 and 1, indicating
397 an overall excellent performance of this modelling framework.

398 *Table 3.2.6.1: Accuracy and AUC score for out-of-sample validation of infectious syndrome models (GLOBAL)*

Model	Age group name	Accuracy	AUC score
CAI lower respiratory infections and all related infections in the thorax	Post Neonatal to 5	0.99	1.00
CAI lower respiratory infections and all related infections in the thorax	70+ years	0.99	1.00
CAI urinary tract infections and pyelonephritis	0 to 39	1.00	1.00
CAI urinary tract infections and pyelonephritis	40 plus	1.00	1.00
Diarrhoea	Early Neonatal	1.00	1.00
Diarrhoea	Late Neonatal	1.00	1.00
Diarrhoea	1 to 4	0.99	1.00
Diarrhoea	20 to 24	0.99	1.00
Diarrhoea	25 to 29	0.99	1.00
Diarrhoea	30 to 34	0.99	1.00
Diarrhoea	35 to 39	0.99	1.00
CAI lower respiratory infections and all related infections in the thorax	5 to 69	0.99	0.99
Diarrhoea	Post Neonatal	0.98	0.99
Diarrhoea	5 to 9	0.99	0.99
Diarrhoea	10 to 14	0.99	0.99
Diarrhoea	15 to 19	0.99	0.99
Diarrhoea	40 to 44	0.99	0.99
Diarrhoea	45 to 49	0.99	0.99
Diarrhoea	95 plus	0.99	0.99
Meningitis and other bacterial central nervous system infections	Early Neonatal	0.99	0.99
Meningitis and other bacterial central nervous system infections	Late Neonatal	1.00	0.99
Bacterial infections of the skin and subcutaneous systems	Late Neonatal	0.99	0.98
Diarrhoea	50 to 54	0.99	0.98
Diarrhoea	85 to 89	0.99	0.98
Diarrhoea	90 to 94	0.99	0.98
Endocarditis and other cardiac infections	Early Neonatal	0.99	0.98
Endocarditis and other cardiac infections	Late Neonatal	0.99	0.98
Endocarditis and other cardiac infections	85 to 89	0.99	0.98
Endocarditis and other cardiac infections	90 to 94	0.99	0.98
Endocarditis and other cardiac infections	95 plus	0.99	0.98
Meningitis and other bacterial central nervous system infections	Post Neonatal	0.99	0.98
Meningitis and other bacterial central nervous system infections	1 to 4	0.98	0.98
Meningitis and other bacterial central nervous system infections	10 to 14	0.97	0.98
Meningitis and other bacterial central nervous system infections	25 to 29	0.99	0.98
Meningitis and other bacterial central nervous system infections	30 to 34	0.99	0.98
Peritoneal and intra-abdominal infections	25 to 29	0.98	0.98
Peritoneal and intra-abdominal infections	30 to 34	0.98	0.98

Peritoneal and intra-abdominal infections	35 to 39	0.98	0.98
Peritoneal and intra-abdominal infections	80 to 84	0.98	0.98
Peritoneal and intra-abdominal infections	85 to 89	0.98	0.98
Peritoneal and intra-abdominal infections	90 to 94	0.98	0.98
Peritoneal and intra-abdominal infections	95 plus	0.99	0.98
Bacterial infections of the skin and subcutaneous systems	95 plus	0.98	0.97
Diarrhoea	55 to 59	0.99	0.97
Diarrhoea	60 to 64	0.99	0.97
Diarrhoea	75 to 79	0.99	0.97
Diarrhoea	80 to 84	0.99	0.97
Endocarditis and other cardiac infections	10 to 14	0.99	0.97
Endocarditis and other cardiac infections	25 to 29	0.99	0.97
Endocarditis and other cardiac infections	30 to 34	0.99	0.97
Endocarditis and other cardiac infections	35 to 39	0.99	0.97
Endocarditis and other cardiac infections	40 to 44	0.99	0.97
Endocarditis and other cardiac infections	80 to 84	0.99	0.97
Meningitis and other bacterial central nervous system infections	5 to 9	0.97	0.97
Meningitis and other bacterial central nervous system infections	15 to 19	0.98	0.97
Meningitis and other bacterial central nervous system infections	20 to 24	0.99	0.97
Meningitis and other bacterial central nervous system infections	35 to 39	0.99	0.97
Peritoneal and intra-abdominal infections	Early Neonatal	0.99	0.97
Peritoneal and intra-abdominal infections	Late Neonatal	0.99	0.97
Peritoneal and intra-abdominal infections	1 to 4	0.99	0.97
Peritoneal and intra-abdominal infections	5 to 9	0.98	0.97
Peritoneal and intra-abdominal infections	20 to 24	0.97	0.97
Peritoneal and intra-abdominal infections	40 to 44	0.97	0.97
Peritoneal and intra-abdominal infections	75 to 79	0.97	0.97
Bacterial infections of the skin and subcutaneous systems	90 to 94	0.98	0.96
Bloodstream infections	Early Neonatal	0.94	0.96
Bloodstream infections	Late Neonatal	0.95	0.96
Bloodstream infections	Post Neonatal	0.93	0.96
CAI lower respiratory infections and all related infections in the thorax	Neonatal	0.95	0.96
Diarrhoea	65 to 69	0.99	0.96
Diarrhoea	70 to 74	0.99	0.96
Endocarditis and other cardiac infections	15 to 19	0.99	0.96
Endocarditis and other cardiac infections	20 to 24	0.99	0.96
Endocarditis and other cardiac infections	45 to 49	0.99	0.96
Endocarditis and other cardiac infections	50 to 54	0.99	0.96
Endocarditis and other cardiac infections	70 to 74	0.99	0.96
Endocarditis and other cardiac infections	75 to 79	0.99	0.96
Meningitis and other bacterial central nervous system infections	40 to 44	0.99	0.96

Meningitis and other bacterial central nervous system infections	45 to 49	0.99	0.96
Peritoneal and intra-abdominal infections	10 to 14	0.97	0.96
Peritoneal and intra-abdominal infections	15 to 19	0.96	0.96
Peritoneal and intra-abdominal infections	45 to 49	0.97	0.96
Peritoneal and intra-abdominal infections	70 to 74	0.97	0.96
Bacterial infections of the skin and subcutaneous systems	30 to 34	0.99	0.95
Bacterial infections of the skin and subcutaneous systems	85 to 89	0.98	0.95
Bloodstream infections	1 to 4	0.91	0.95
Bloodstream infections	95 plus	0.94	0.95
Endocarditis and other cardiac infections	5 to 9	0.99	0.95
Endocarditis and other cardiac infections	55 to 59	0.99	0.95
Endocarditis and other cardiac infections	60 to 64	0.99	0.95
Endocarditis and other cardiac infections	65 to 69	0.99	0.95
Infections of bone, joints, and related organs	10 to 14	0.99	0.95
Infections of bone, joints, and related organs	95 plus	0.99	0.95
Peritoneal and intra-abdominal infections	50 to 54	0.96	0.95
Peritoneal and intra-abdominal infections	55 to 59	0.96	0.95
Peritoneal and intra-abdominal infections	60 to 64	0.96	0.95
Peritoneal and intra-abdominal infections	65 to 69	0.96	0.95
Bacterial infections of the skin and subcutaneous systems	Early Neonatal	0.99	0.94
Bacterial infections of the skin and subcutaneous systems	25 to 29	0.99	0.94
Bacterial infections of the skin and subcutaneous systems	35 to 39	0.99	0.94
Bacterial infections of the skin and subcutaneous systems	40 to 44	0.98	0.94
Bacterial infections of the skin and subcutaneous systems	80 to 84	0.98	0.94
Bloodstream infections	5 to 9	0.87	0.94
Bloodstream infections	20 to 24	0.89	0.94
Bloodstream infections	25 to 29	0.92	0.94
Bloodstream infections	30 to 34	0.93	0.94
Endocarditis and other cardiac infections	1 to 4	0.99	0.94
HAI lower respiratory infections and all related infections in the thorax	Post Neonatal to 5	0.97	0.94
Infections of bone, joints, and related organs	0 to 9	0.99	0.94
Infections of bone, joints, and related organs	85 to 89	0.99	0.94
Infections of bone, joints, and related organs	90 to 94	0.99	0.94
Meningitis and other bacterial central nervous system infections	50 to 54	0.99	0.94
Peritoneal and intra-abdominal infections	Post Neonatal	0.98	0.94
Bacterial infections of the skin and subcutaneous systems	20 to 24	0.99	0.93
Bacterial infections of the skin and subcutaneous systems	45 to 49	0.98	0.93
Bacterial infections of the skin and subcutaneous systems	75 to 79	0.98	0.93
Bloodstream infections	35 to 39	0.92	0.93
Bloodstream infections	90 to 94	0.94	0.93
Infections of bone, joints, and related organs	80 to 84	0.99	0.93

Meningitis and other bacterial central nervous system infections	55 to 59	0.99	0.93
Meningitis and other bacterial central nervous system infections	60 to 64	0.99	0.93
Meningitis and other bacterial central nervous system infections	90 to 94	0.99	0.93
Bacterial infections of the skin and subcutaneous systems	50 to 54	0.98	0.92
Bacterial infections of the skin and subcutaneous systems	55 to 59	0.97	0.92
Bacterial infections of the skin and subcutaneous systems	60 to 64	0.97	0.92
Bacterial infections of the skin and subcutaneous systems	65 to 69	0.97	0.92
Bacterial infections of the skin and subcutaneous systems	70 to 74	0.98	0.92
Bloodstream infections	10 to 14	0.85	0.92
Bloodstream infections	40 to 44	0.90	0.92
Bloodstream infections	85 to 89	0.93	0.92
Infections of bone, joints, and related organs	75 to 79	0.99	0.92
Meningitis and other bacterial central nervous system infections	65 to 69	0.99	0.92
Meningitis and other bacterial central nervous system infections	70 to 74	0.99	0.92
Meningitis and other bacterial central nervous system infections	80 to 84	0.99	0.92
Meningitis and other bacterial central nervous system infections	85 to 89	0.99	0.92
Meningitis and other bacterial central nervous system infections	95 plus	0.99	0.92
Bloodstream infections	15 to 19	0.84	0.91
Bloodstream infections	80 to 84	0.92	0.91
Infections of bone, joints, and related organs	70 to 74	0.99	0.91
Meningitis and other bacterial central nervous system infections	75 to 79	0.99	0.91
Bacterial infections of the skin and subcutaneous systems	15 to 19	0.98	0.90
Bloodstream infections	45 to 49	0.89	0.90
Infections of bone, joints, and related organs	60 to 64	0.99	0.90
Infections of bone, joints, and related organs	65 to 69	0.99	0.90
Bacterial infections of the skin and subcutaneous systems	Post Neonatal	1.00	0.89
Bloodstream infections	50 to 54	0.88	0.89
Bloodstream infections	75 to 79	0.91	0.89
Endocarditis and other cardiac infections	Post Neonatal	0.99	0.89
HAI lower respiratory infections and all related infections in the thorax	5 to 69	0.96	0.89
HAI lower respiratory infections and all related infections in the thorax	70+ years	0.96	0.89
Infections of bone, joints, and related organs	55 to 59	0.99	0.89
Bloodstream infections	70 to 74	0.90	0.88
Infections of bone, joints, and related organs	15 to 19	0.99	0.88
Infections of bone, joints, and related organs	50 to 54	0.99	0.88
Bacterial infections of the skin and subcutaneous systems	1 to 4	1.00	0.87
Bacterial infections of the skin and subcutaneous systems	5 to 9	0.99	0.87
Bacterial infections of the skin and subcutaneous systems	10 to 14	0.99	0.87
Bloodstream infections	55 to 59	0.88	0.87
Bloodstream infections	60 to 64	0.88	0.87
Bloodstream infections	65 to 69	0.89	0.87

HAI urinary tract infections and pyelonephritis	40 plus	0.99	0.86
Infections of bone, joints, and related organs	25 to 29	0.99	0.85
Infections of bone, joints, and related organs	35 to 39	0.99	0.85
Infections of bone, joints, and related organs	40 to 44	0.99	0.84
Infections of bone, joints, and related organs	45 to 49	0.99	0.84
Infections of bone, joints, and related organs	30 to 34	0.99	0.83
Infections of bone, joints, and related organs	20 to 24	0.99	0.82
HAI urinary tract infections and pyelonephritis	0 to 39	0.99	0.77
HAI lower respiratory infections and all related infections in the thorax	Neonatal	0.99	0.50

399

400

Table 3.2.6.2: Accuracy and AUC score for out-of-sample validation of sepsis models (GLOBAL)

Model	Age group name	Accuracy	AUC score
Sepsis	25 to 29	0.94	0.95
Sepsis	15 to 19	0.95	0.94
Sepsis	20 to 24	0.95	0.94
Sepsis	30 to 34	0.93	0.94
Sepsis	1 to 4	0.89	0.93
Sepsis	35 to 39	0.93	0.93
Sepsis	5 to 9	0.89	0.92
Sepsis	10 to 14	0.90	0.92
Sepsis	95 plus	0.96	0.92
Sepsis	40 to 44	0.93	0.91
Sepsis	90 to 94	0.96	0.90
Sepsis	Post Neonatal	0.88	0.89
Sepsis	Late Neonatal	0.87	0.88
Sepsis	45 to 49	0.93	0.88
Sepsis	85 to 89	0.96	0.88
Sepsis	Early Neonatal	0.91	0.87
Sepsis	80 to 84	0.96	0.87
Sepsis	50 to 54	0.93	0.86
Sepsis	75 to 79	0.95	0.85
Sepsis	55 to 59	0.94	0.84
Sepsis	70 to 74	0.95	0.84
Sepsis	60 to 64	0.94	0.83
Sepsis	65 to 69	0.94	0.83

401

402 Section 3.3: Case fatality ratios*403 Section 3.3.1: Input data*

404 Case fatality ratios (CFRs) were modelled for the pathogens and infectious syndromes of interest using all available
 405 data detailing the organism responsible for infection, the infectious syndrome, and patient outcome, which included
 406 hospital and microbial data. Input data for the CFR models were aggregated based on data source, year, GBD
 407 location, and age group (as well as hospital/community acquired status, in the case of the lower respiratory and

408 urogenital infectious models). For lower respiratory and blood stream infections, for which CFRs could be vastly
409 different in neonates, we modelled the following age groups: neonatal, post-neonatal–5 years, 5–50 years, 50–70
410 years, and 70 years and older. For all other infectious syndromes, we modelled the following age groups: neonatal–5
411 years, 5–50 years, 50–70 years, and 70 years and older. We excluded from the analysis any source-location-year-age
412 with fewer than five cases and zero deaths.

413
414 To allow us to implement linear models, CFRs were logit-transformed. We used the delta method to compute the
415 standard error of CFRs in logit space. To incorporate data with zero deaths, or with an equal number of deaths and
416 cases, we applied a 1% offset, such that the CFRs for data with zero deaths was represented as 1% and the CFR for
417 data with an equal number of deaths and cases was represented as 99%.

418 Pathogen-specific CFRs were modelled separately by infectious syndrome and were calculated as a function of
419 HAQ Index and age. To account for heterogeneity across the sources of input data, we implemented a mixed-effects
420 meta-regression framework, modelling data source as a random effect. We further incorporated a binary fixed-effect
421 denoting whether the data source only included intensive care unit (ICU) patients, for which CFRs were expected to
422 be higher. The pathogens of interest for each infectious syndrome were determined by prevalence in the data and
423 expert opinion, with the goal of modelling approximately 90% of specified-pathogens associated with each
424 infectious syndrome.

425 *Section 3.3.2: Models run for each infectious syndrome*

426 The interaction of the HAQ Index fixed-effect with the pathogen-specific fixed-effect allowed the relative
427 deadliness of pathogens to vary depending on a location's HAQ Index – this is termed an ‘interaction model’. For
428 those pathogens with fewer than ten high quality data points below 0.7 HAQ Index, or those whose results in the
429 interaction models indicated an unrealistically large influence of HAQ Index (eg, 70% CFR in low HAQ Index
430 countries, 1% CFR in high HAQ Index countries), we modelled a pathogen-specific intercept with an HAQ Index
431 fixed-effect shared across the pathogens. As a consequence of the single fixed-effect on HAQ Index, a pathogen that
432 was predicted to be the deadliest in low HAQ Index countries would also be predicted to be the deadliest in high
433 HAQ Index countries in these ‘intercept models.’ To estimate the CFRs for other known bacteria, which either were
434 not selected as a pathogen of interest or lacked sufficient data for inclusion in the intercept models, we pooled all
435 bacterial data together and estimated a single CFR curve from age, HAQ Index, and the data source heterogeneity
436 covariates. Thus, up to three models were run for each infectious syndrome:

- 437 1. an interaction model including data for all data rich pathogens and ‘other specified bacteria’ (which was
438 included to inform the overall influence of HAQ Index on CFR, predictions were only generated for the
439 data rich pathogens),
- 440 2. an intercept model including data for data rich and data sparse pathogens, as well as ‘other specified
441 bacteria’ (predictions were only generated for the data sparse pathogens), and
- 442 3. an ‘other bacteria’ model that included data for all bacterial pathogens (predictions were generated by HAQ
443 Index and age, without any pathogen specific term).

444 For some infectious syndromes, the relative deadliness of a pathogen may be strongly determined by either the age
445 of the patient or whether the infection was community- or hospital-acquired. For bloodstream infections, we ran two
446 distinct sets of CFR models, one for neonates (0–27 days) and another for post neonates, to capture the differing
447 dynamics of pathogen deadliness in these two populations. As is done for our other modelling processes, we also
448 separate community-acquired and hospital-acquired cases in our CFR models for lower respiratory and urogenital
449 infections. Because some data sources did not provide enough information to infer whether an infection was
450 community- or hospital-acquired, but still included important information on the relative pathogenesis and the
451 difference in CFRs across varying HAQ indices, infections of unknown origin were included in both the
452 community-acquired and hospital-acquired models for these two syndromes. Any bias in these ‘unknown origin’
453 infections was adjusted for using a binary fixed-effect representing an ‘unknown origin’ infection, and predictions
454 were generated for the community- and hospital-acquired infections only.

455 *Section 3.3.3: Modelling framework*

456 The data were analysed using a meta-analytic mixed effects structure. The main model can be specified as follows:

- 457 $logit(y_i) = X_i\beta + u_i 1 + \epsilon_i, \quad \epsilon_i \sim N(0, \Sigma_i), \quad u_i \sim N(0, \gamma)$
- 458 where
- 459 • y_i contains CFRs for data source i
 460 • Design matrix contains as columns the following covariates
 o in all models:
 ▪ HAQ Index
 ▪ dummy-coded indicator for age group
 ▪ dummy-coded ICU indicator for data source (1 if data source only compiles information on ICU patients, 0 if a mix between ICU/non-ICU patients)
 o in ‘interaction’ and ‘intercept’ models:
 ▪ dummy-coded indicator for pathogen
 o in ‘interaction’ models only:
 ▪ interaction between pathogen and HAQ Index (product of dummy-coded pathogen columns and HAQ Index)
 o in models evaluating community/hospital acquired infection (LRI+, UTI):
 ▪ dummy-coded variable indicating source of infection (1 if unknown source, 0 if community OR hospital acquired, depending on whether the model is evaluating community or hospital infections)
- 475 • β are fixed effect multipliers
 476 • ϵ_i are observation error terms with known variances
 477 • u_i are data source-specific random intercepts with unknown covariance γ

478 The underlying program used to fit the model (meta-regression, Bayesian, regularized, trimmed [MR-BRT]) is
 479 described elsewhere.⁷ The program allows specification of priors on γ and β , which were particularly useful when
 480 data for specific locations was very limited.

481 *Section 3.3.4: Predictions and uncertainty*
 482 Predictions for 2019 CFRs were generated for each country, age group, and pathogen as a function of each country’s
 483 HAQ Index, assuming mixed ICU/non-ICU patients and, in the case of models for UTI and LRI+, that the infection
 484 was community- or hospital-acquired (in contrast to infections of unknown origin). For pathogens with insufficient
 485 data to estimate a syndrome-specific CFR, we predicted out using the ‘other bacteria’ CFR associated with the
 486 infectious syndrome. Importantly, all of the CFRs we calculate by infectious syndrome are independent of that
 487 syndrome’s underlying cause.

488 Uncertainty estimates were generated using asymptotic uncertainty intervals. Specifically, for the model, the
 489 posterior uncertainty for the coefficients β is Gaussian, with mean and variance given below:

$$490 \quad \hat{\beta} = (\sum_i X_i^T V_i^{-1} X_i)^{-1} (\sum_i X_i^T V_i^{-1} logit(y_i))$$

$$491 \quad Var(\hat{\beta}) = (\sum_i X_i^T V_i^{-1} X_i)^{-1}$$

492 where

$$493 \quad V_i = 11^T + \hat{\gamma} I$$

494 where $\hat{\gamma}$ is the estimated variance of random effects and $Var(\hat{\beta})$ refers to the estimated variance-covariance matrix
 495 of beta.

496 The variance-covariance matrix was used to obtain 1000 draws for the coefficients, which are then used to get
 497 intervals for the predictions.

498 *Section 3.3.5: Modeling exceptions for lower respiratory infections and all related infections in the thorax*

499 To reduce the effect of bias from severe cases, we controlled for data provided from ICU-only sources which, if left
500 uncontrolled, bias the results towards higher CFRs. Additionally, we controlled for data with unknown setting of
501 infection origin due to our process of modeling community- and hospital-acquired lower respiratory infections
502 separately.

503 We used a Poisson family model in which the probability distribution took the form of:

$$504 P(y_i|\lambda_i) = \frac{1}{y_i!} \exp(-\lambda_i) \lambda_i^{y_i} = \frac{1}{y_i!} \exp(-\lambda_i + y_i \log(\lambda_i))$$

505 Where y is the number of deaths. This suggests the following parameterization of:

$$506 \log(\lambda_i) = c_i + x_i^T \beta.$$

507 The link function is the exponential map and $x_i^T \beta$ is a linear predictor that can use direct covariates or splines. c_i is
508 an offset used for observation-specific normalization of the number of cases, thereby allowing us to model rates.

509 β is estimated using the following:

$$510 \min_{\beta} \sum_i \exp(c_i + x_i^T \beta) - y_i(c_i + x_i^T \beta)$$

511 And the following priors were used to constrain the coefficients:

- 512 • Pathogen-vaccination interaction: We assumed vaccination would have no impact on CFRs of unrelated
513 pathogens. For all combinations of pathogen-vaccination interaction that were not *Streptococcus*
514 *pneumoniae*:PCV vaccination or *Haemophilus influenzae*:Hib vaccination, we coerced the the coefficients
515 to 0 using model priors. For the *Streptococcus pneumoniae*:PCV vaccination and *Haemophilus*
516 *influenzae*:Hib vaccination interaction terms, we employed a negativity prior to enforce case-fatality rates
517 for these pathogens to decrease as vaccination was introduced.
- 518 • Large data source dummy variables: A variable for the data source was included to account for source
519 heterogeneity. It is important to note that many input data sources covered only a single country, leading to
520 low variability in HAQ Index within each data source. Such collinearity adversely influenced the accuracy
521 of the estimated effect of HAQ Index, which was instrumental in extrapolating trends from the input data to
522 global results. To emphasise the contribution of HAQ Index over data-source in the modelled estimates, we
523 implemented a Gaussian prior (mean 0, standard error 0.1) on the coefficients for data source variables.

524
525 Nonfatal pathogen proportions for a given demographic group and pathogen were converted to deaths using the
526 CFRs estimates for demographic group as follows:

$$527 p_{i,j}^{deaths} = \frac{p_{i,j} \times CFR_i}{\sum_{J_{i,j}} CFR_i}$$

528 Finally, we adjusted influenza and RSV mortality estimates for 2020 and 2021 to account for the reductions in
529 influenza and RSV cases associated with the COVID-19 pandemic, as described elsewhere in this appendix.

530

531 **Section 3.4: Pathogen distribution**

532 *Section 3.4.1: Input data and pathogens selected for estimation*

533 With this model, we aimed to estimate the distribution of pathogens causing each infectious syndrome. To get input
534 data for this model, we gathered all available data sources described in section 2 that meet the following criteria:

- 535 • Sufficient diagnosis (for patient- or admission-level datasets) or sample specimen type (for isolate- or
536 culture-level datasets) information for us to determine the infectious syndrome

- 537 • Information on which pathogen(s) caused the infection or which pathogen(s) were detected in an infectious
538 sample, as determined through culture or genomic-based methods
539 • Did not have a strongly biased sampling framework across pathogens (for example, did not deliberately
540 sample until 100 cases of every pathogen of interest had been obtained)

541 The input data source types that met these criteria in this study were:

- 542 • Multiple causes of death data
543 • Hospital discharge
544 • Linkage data
545 • Microbial data with and without outcome information
546 • Literature studies from the aetiology literature reviews

547 For each infectious syndrome, we selected roughly 10–20 pathogens to estimate explicitly in the pathogen
548 distribution based on the following criteria:

- 549 • The prevalence of each pathogen in the raw data
550 • Clinical knowledge about the primary aetiologies of each infectious syndrome
551 • The amount of available data, which limits the number of pathogens that can be estimated successfully

552 In addition to the n pathogens for a given syndrome that we estimate explicitly, we also included an “other specified
553 pathogens” category for every infectious syndrome, to which we mapped all other aetiologies identified in the data.
554 Thus, the set of estimated pathogens for each infectious syndrome is mutually exclusive and collectively exhaustive
555 of all possible aetiologies. Polymicrobial infections were either estimated explicitly or included in the “other”
556 category, making all explicitly estimated individual pathogens mono-pathogenic. In addition to these criteria, we
557 also considered the following factors:

- 558 • Since we were ultimately interested in estimating the burden of AMR in bacteria, we erred on the side of
559 estimating bacteria with strong evidence of AMR, rather than bacteria with low evidence of AMR or non-
560 bacterial aetiologies.
561 • Clinically relevant aetiologies differ from syndrome to syndrome, and we were unable to estimate all
562 pathogens explicitly in every syndrome due to a lack of data. Therefore, the “other” pathogen category is
563 composed of slightly different pathogens for every infectious syndrome and can occasionally contain
564 pathogens that are explicitly estimated for another infectious syndrome. We attempted to mitigate this by
565 including bacteria with strong evidence of AMR in the estimation of all infectious syndromes whenever
566 possible.
567 • We included enough explicitly estimated pathogens to ensure that the “other” category remained below
568 10% for all infectious syndromes.

569 For a list of pathogens covered in each infectious syndrome model, please refer to table 3.4.6 (pp 23-24).

570 *Section 3.4.2: Data processing and analysis*

571 We extracted and standardised the location, year, age, sex, diagnoses, specimen type, pathogens, and hospital- and
572 community-acquired (HAI and CAI) status of each record in every dataset. These datasets report a variety of
573 metrics, including deaths, admissions, cases, cultures, and isolates. While these metrics are not completely
574 comparable (for example, a single patient may often have multiple cultures taken during a single hospital
575 admission), we chose to standardise them into two categories: “deaths,” for any unit associated with an outcome of
576 death, and “cases,” for any unit regardless of outcome. After standardising the data, we mapped every sample ID or
577 tabulated figure in the data to infectious syndrome based on its diagnoses and specimen type. More details on this
578 process can be found the appendix of Murray et al. (2022).¹

579 Some pathogens cause disease so rarely or are so commonly contaminants that we considered them to be
580 contaminants, unlikely to be the true cause of disease. Examples include many *Corynebacterium* species and
581 *Staphylococcus epidermidis*. We dropped all such contaminants from the analysis, as well as any record listed by
582 treating clinicians in the data as a contaminant. We also dropped from the analysis all records where no pathogen
583 was detected, or the patient diagnosis indicated an unspecified bacterium. This assumes that the distribution of
584 pathogens among cases with known aetiology are the same as those with unknown aetiology; in other words that the

585 probability of detection is the same for every pathogen. This assumption may break down if certain pathogens are
586 more difficult to detect than others, or in cases where a pathogen is irregularly tested for within a laboratory.

587 For data sources where multiple pathogens were listed per sample ID, we classified these cases according to the
588 following criteria. First, if a case contained more than one of “unspecified bacteria,” “virus,” “fungus,” and another
589 pathogen(s), we chose to drop all these pathogens except the one(s) most likely to be responsible for disease, with
590 the following ranking from most to least likely: 1. Another pathogen(s); 2. Unspecified bacteria; 3. Virus; 4. Fungus.
591 This was to drop co-occurrence profiles that we consider to be uninformative, like a viral infection co-occurring
592 with a fungal infection. After applying this drop, we considered any sample ID that contained more than one
593 pathogen to be polymicrobial. Polymicrobial was treated as a distinct pathogen category in all further analysis, and
594 we were unable to include any AMR burden from polymicrobial infections in our final results, which possibly
595 underestimates the burden of AMR by hiding infections caused by resistant pathogens of interest in the
596 polymicrobial category.

597 Furthermore, in our approach we chose to assume that the relative prevalences of pathogens in datasets that do not
598 report co-occurrence would be comparable to their mono-pathogenic counterparts in datasets that do report co-
599 occurrence. This assumes that the co-occurrence of pathogens is random and is not correlated for certain pathogens.
600 We did not have sufficient data to fully test the validity of this assumption, given that few datasets report the full
601 universe of pathogens which may co-occur. When selecting pathogens for estimation, we took into account that the
602 set of estimated pathogens for each infectious syndrome is mutually exclusive and collectively exhaustive of all
603 possible aetiologies. Polymicrobial infections were either estimated explicitly or included in the “other” category,
604 making all explicitly estimated individual pathogens mono-pathogenic. Additional factors that were considered can
605 be found in the appendix of Murray et al. (2022).¹

606 *Section 3.4.3: Dealing with challenges in pathogen distribution appraisal*

607 One of the central challenges of estimating pathogen distributions was that not every data source tested for or
608 reported every possible aetiology of a given infectious syndrome. For example, many literature studies on the
609 aetiologies of meningitis only report on bacterial aetiologies, and some surveillance systems only collect data on
610 certain pathogens of interest. Only certain pathogens are referenced explicitly in the International Classification of
611 Diseases (ICD), limiting which pathogens can be identified from ICD-based data types like MCoD and hospital
612 discharge. Finally, some datasets reported only a subset of the pathogens that we are interested in for a given
613 infectious syndrome, reporting the remaining aetiologies in an aggregate “other” category. These practices have led
614 to inconsistencies in the “other” and “polymicrobial” categories across data sources. Datasets can either over or
615 under-report “other,” and datasets that report fewer specific pathogens will automatically report fewer polymicrobial
616 infections.

617 To address this problem, we maintained a list of data sources that we believe have sufficient testing and reporting to
618 give unbiased estimates of other and polymicrobial for all syndromes, dropping any data on polymicrobial or other
619 that did not come from these data sources. These data sources all had a complete sampling framework (eg, they do
620 not limit the scope of aetiologies that they test for) and reported their results without any deliberate aggregation.
621 While we believe this list provided an accurate starting place for the estimation of other and polymicrobial, future
622 work to improve this method would involve a more detailed analysis of sampling framework and reporting
623 categories in each dataset, specific to each infectious syndrome.

624 There were two major exceptions to this method for handling “other specified pathogens.” First, determining the
625 pathogenic aetiology of LRI with microbiology represents challenges that have been well described previously.^{8,9} In
626 order to account for this limitation, we utilised a vaccine probe design to inform the *Streptococcus pneumoniae*
627 cause fraction of LRI, consistent with the approach used in the GBD aetiology estimation process.^{10,11} In brief, we
628 extracted the vaccine efficacy of the pneumococcal vaccine against all pneumonia from 18 vaccine probe studies
629 with randomised-control trial, before-after, and cohort designs among children and adults. We then calculated the
630 PAF of pneumonia due to *S. pneumoniae* in each study (*Strep Base PAF*) based on these vaccine efficacies
631 ($VE_{all pneumonia}$), the vaccine efficacy of pneumococcal vaccine against vaccine-type pneumococcal pneumonia as
632 pooled from three studies (two in children and one in adults) (VE_{vtp}), the percentage of the population covered by
633 the pneumococcal vaccine as modelled in GBD (100% for RCTs) (Cov_{PCV3}),¹¹ and the percent of serotypes covered

634 by the vaccine¹² $Cov_{serotype}$ (equation 6.2.6.1). We modelled a global age-specific PAF for *S. pneumoniae* based
635 on these data in the MR-BRT environment and finally adjusted this PAF based on the vaccine coverage in children
636 in every GBD location in 2019 and optimal vaccine efficacy in children (*Strep Final PAF*) (equation 3.4.3.2). In
637 adults (age 5+), we assumed the effects of vaccination on adults would be primarily indirect from vaccination in
638 children, and included an adjustment factor on the vaccine efficacy to account for this, derived from Grijalva et al.¹³

639
$$Strep\ Base\ PAF = \frac{VE_{all\ pneumonia}}{VE_{vtp} Cov_{PCV3} Cov_{serotype}} \quad (3.4.3.1)$$

640
$$Strep\ Final\ PAF = \frac{Strep\ Base\ PAF(1 - Cov_{PCV3} Cov_{serotype} VE_{PCV3\ optimal})}{1 - (Strep\ Base\ PAF) Cov_{PCV3} Cov_{serotype} VE_{PCV3\ optimal}} \quad (3.4.3.2)$$

641

642 In this vaccine probe analysis, $(1 - Strep\ Final\ PAF)$ is not consistent with the “other” category in our model,
643 since it includes all non-*S. pneumoniae* aetiologies. We retained all of the data from the vaccine probe analysis as
644 two categories, *S. pneumoniae* and “not *S. pneumoniae*” and addressed the inconsistencies between them and our
645 other data using our modelling framework.

646 The second major exception involves several literature studies on the proportion of neonatal bacterial meningitis
647 caused by *Streptococcus agalactiae* (Group B *Streptococcus*; GBS). We found that these literature studies were
648 important to our estimation of the pathogen distribution of neonatal meningitis, which is distinct from other age
649 groups because of its high proportion of GBS. However, these studies either only reported or were only extracted
650 with two categories, GBS and “other bacterial, not GBS.” We retained both these categories and addressed the
651 inconsistencies between them and our other data using our modelling framework.

652 *Section 3.4.4: Age-sex splitting and standardizing measures*

653 We standardised age and sex across all datasets to the following most-detailed groups using the GBD causes of
654 death age-sex splitting algorithm for age:¹⁴ 0–6, 7–27, and 28–364 days, and 1–4, 5–9, 10–14, 15–19, 20–24, 25–29,
655 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, 65–69, 70–74, 75–79, 80–84, 85–89, 90–94, 95+ years; and sex:
656 male and female. This algorithm assumes that age-sex pattern of the death or case rate for a given infectious
657 syndrome or pathogen is inherent to the pathology of the disease and is therefore constant across location and year.
658 Details on how the algorithm was applied can be found in the appendix of Murray et al. (2022).¹

659 The input data sources reported a variety of combinations of measures, including some that reported deaths only,
660 some that reported cases only, and some that reported both cases and deaths. In order to standardise these measures
661 to cases, we estimated infectious syndrome- and pathogen-specific CFRs and used these CFRs to convert all deaths-
662 only datasets to cases. For any infectious syndrome or pathogen combination for which we did not have enough data
663 to estimate plausible CFRs, we used a set of all-bacteria CFRs for that infectious syndrome instead. All modelling
664 was done in case space.

665 Several of our microbial databases came exclusively from ICUs and were therefore heavily biased towards severe
666 illness. In order to mitigate this bias, we dropped all information on cases in ICU-only datasets and recalculated
667 implied cases based on reported deaths and our CFRs. No similar adjustment was made to attempt to account for
668 biases between hospitalised and un-hospitalised populations, although we did account for HAI versus CAI for two
669 infectious syndromes – LRI and thorax infections and UTI – within our modelling framework. The use of hospital-
670 based data to calculate both pathogen-specific case fatality ratios and pathogen distributions biases our estimate of
671 the distribution of pathogens in incident cases towards more severe disease, particularly for less-severe infectious
672 syndromes like lower respiratory infections; adjusting for this bias would improve the accuracy of our non-fatal
673 estimates.

674 *Section 3.4.5: Modelling framework*

675 To model the distribution of pathogens for each infectious syndrome, we developed a method for the multinomial
676 estimation of partial and compositional observations (MEPCO). We assumed that the aetiologies of a given
677 infectious syndrome followed a multinomial distribution. Due to inconsistencies in which pathogens are tested for

and reported by different data sources, each data source contained partial observations of the possible outcomes of the underlying multinomial distribution. Certain data sources like the vaccine probe estimates and the GBS neonatal meningitis studies represent compositional observations, where pathogens like “not *S. pneumoniae*” and “other bacterial, not GBS” represent aggregates of more detailed pathogens.

In order to use both partial and compositional data, we constructed a network model with the dependent variable as the log ratio of cases between different pathogens and estimated over a flexible parameterisation of multinomial parameters using a maximum likelihood approach. Consider a given infectious syndrome with a multinomial distribution of n mutually exclusive, collectively exhaustive aetiologies with probabilities $p = (p_1, \dots, p_n)$, so that each $p_j \in (0,1)$ and $\sum_j p_j = 1$. The likelihood of an observation of $c = (c_1, \dots, c_n)$, where c_j = number of cases of pathogen j in a total sample of N infections ($\sum_j c_j = N$), is:

$$P(c|p) = N! \prod_{j=1}^n \frac{p_j^{c_j}}{c_j!}$$

We modelled the probabilities as proportional to a link function with a linear predictor:

$$p_{i,j} \propto \exp(x_{i,j}^T \beta_j)$$

for observations i , a vector of covariates $x_{i,j}$, and a vector of coefficients β_j for each pathogen j . the appendix of Murray et al. (2022)¹ contains a table with the covariates used for infectious syndrome model, which included a typical specification included an intercept term, HAQ Index, a categorical age group dummy for large age bins, and any relevant vaccine coverage proportions by country. However, we did not observe these probabilities directly. Rather, we observed ratios between sums of these probabilities, which reduce to ratios between sums of cases within each study. These observations therefore take the form:

$$y_i = \frac{\text{cases of pathogen A}}{\text{cases of pathogen B}} = \frac{\sum_{j=1}^n w_{i,j}^a \exp(x_{i,j}^T \beta_j)}{\sum_{j=1}^n w_{i,j}^b \exp(x_{i,j}^T \beta_j)}$$

where $w_{i,j}^a$ is a weight of 0 or 1 that selects the mutually exclusive, collectively exhaustive most-detailed pathogens that make up observed pathogen A, which may be a composite observation. For example, for the “other bacterial, non-GBS” pathogen, $w_{i,j}$ would be 1 for *Staphylococcus aureus*, *S. pneumoniae*, *Haemophilus influenzae*, *Neisseria meningitidis*, *Listeria monocytogenes*, *K. pneumoniae*, *E. coli*, and other pathogens and 0 for GBS and virus. We dropped all observations where either the numerator or denominator had 0 observed cases in order to make this calculation and a forthcoming log transform possible. This may bias the model towards overestimating less common pathogens.

It is not possible to infer all coefficients β_j from the observations, since they are all relative. However, if we fix all of the coefficients for one pathogen to 0 as a reference group, then we obtain a well-posed inverse problem, as long as there is enough data to estimate the remaining coefficients. Without loss of generality, we assumed $\beta_1 = 0$ for all elements and obtain estimates of the remaining β_2, \dots, β_n by minimising the sum of the residuals between log-transformed observations y and corresponding log-transformed predictions from equation 3.3.5.4:

$$\min_{\beta_2, \dots, \beta_n} f(\beta) := \sum_i \frac{1}{\sigma_i^2} \left[\ln(y_i) - \ln \left(\sum_{j=1}^n w_{i,j}^a \exp(x_{i,j}^T \beta_j) \right) + \ln \left(\sum_{j=1}^n w_{i,j}^b \exp(x_{i,j}^T \beta_j) \right) \right]^2 \quad (3.4.5.4)$$

where σ_i^2 are variances corresponding to the data points. Equation 3.3.5.4 is a nonlinear likelihood minimisation problem that we optimised using a standard implementation of the Gauss-Newton method.¹⁵ We then re-normalised the optimal coefficients to obtain final predictions of the probabilities of each pathogen:

715

$$p_{i,j} = \frac{\exp(x_{i,j}^T \beta_j)}{\sum_j \exp(x_{i,j}^T \beta_j)} \quad (3.4.5.5)$$

716 To quantify the uncertainty of this estimate, we used asymptotic statistics to obtain the posterior distribution of
 717 $(\beta_2, \dots, \beta_n)$. Specifically, using the Gauss-Newton Hessian approximation gave us the asymptotic information
 718 matrix for all β_j except for the reference pathogen, allowing us to sample draws of $\beta = (\beta_1 = 0, \beta_2, \dots, \beta_n)$. For
 719 each β draw and given feature x , we obtained a corresponding draw of p using equation 3.3.3.5.

720 Finally, to convert $p_{i,j}$ for a given demographic group i from case space to deaths space, we transformed using our
 721 CFR estimate for demographic i :

722

$$p_{i,j}^{deaths} = \frac{p_{i,j} \times CFR_i}{\sum_j p_{i,j} \times CFR_i} \quad (3.4.5.6)$$

723 This network regression with covariates framework allowed us to use partial and composite data that reported on
 724 one or only a few pathogens, or that reported multiple pathogens aggregated together. Networks, however, can be
 725 unstable with sparse data and stable estimates have in some cases required the use of Bayesian priors in these
 726 models. In particular, we imposed Gaussian priors with mean 0 and non-zero variance on all coefficients except
 727 intercepts, to bias the model away from spurious effects driven by data sparsity. These priors were based on expert
 728 opinion and can improved with further empirical validation in the future (appendix of Murray et al.¹).
 729

730 *Table 3.4.6: Pathogens included in each infectious syndrome model*

Infectious syndrome	Pathogens assessed	Model covariates	Age groups
Bloodstream infections	<i>Acinetobacter baumannii</i> , <i>Citrobacter</i> spp., <i>Enterobacter</i> spp., <i>Enterococcus faecalis</i> , <i>Enterococcus faecium</i> , other enterococci, <i>Escherichia coli</i> , fungus, group A <i>Streptococcus</i> , group B <i>Streptococcus</i> , <i>Klebsiella pneumoniae</i> , <i>Neisseria meningitidis</i> , non-typoidal <i>Salmonella</i> , polymicrobial, <i>Proteus</i> spp., <i>Pseudomonas aeruginosa</i> , <i>Salmonella Typhi</i> , <i>Serratia</i> spp., <i>Staphylococcus aureus</i> , <i>Streptococcus pneumoniae</i>	HAQ Index, ¹⁴ age group, age-standardised proportion of intravenous drug use, ²³ proportion coverage by PCV3 vaccine, ³³ indicator variable for Europe	Neonatal, Post-neonatal–5, 5–50, 50–70, 70+
Infections of bones, joints, and related organs	<i>Enterococcus faecalis</i> , <i>Enterococcus faecium</i> , other enterococci, <i>Escherichia coli</i> , group A <i>Streptococcus</i> , group B <i>Streptococcus</i> , <i>Klebsiella pneumoniae</i> , <i>Pseudomonas aeruginosa</i> , <i>Staphylococcus aureus</i>	HAQ Index, age group	Under 5, 5–50, 50–70, 70+
Endocarditis and other cardiac infections	See bloodstream infection pathogens	Not explicitly modelled. Pathogen distribution for bloodstream infections is used.	Neonatal, Post-neonatal–5, 5–50, 50–70, 70+
Diarrhoea	Adenovirus, <i>Aeromonas</i> spp., Amebiasis, <i>Campylobacter</i> spp., <i>Clostridium difficile</i> , cryptosporidium, enteropathogenic <i>Escherichia coli</i> , enterotoxigenic <i>Escherichia coli</i> , non-typoidal <i>Salmonella</i> , norovirus, rotavirus, <i>Shigella</i> spp., <i>Vibrio cholerae</i>	Not modelled here. GBD diarrhoea aetiology estimates are used.	GBD most detailed age groups
Lower respiratory infections and all related infections in the thorax	<i>Acinetobacter baumannii</i> , <i>Chlamydia</i> spp., <i>Enterobacter</i> spp., <i>Escherichia coli</i> , fungus, group B <i>Streptococcus</i> , <i>Haemophilus influenzae</i> , <i>Klebsiella pneumoniae</i> , <i>Legionella</i> spp., <i>Mycoplasma</i> spp., polymicrobial, <i>Pseudomonas aeruginosa</i> , <i>Staphylococcus aureus</i> , <i>Streptococcus pneumoniae</i> , Influenza viruses, Respiratory syncytial virus, other viruses	HAQ Index, proportion coverage by PCV3 vaccine, proportion coverage by Hib3 vaccine, ³³ age group, HAI/CAI	Neonatal, Post-neonatal–5, 5–50, 50–70, 70+
Meningitis and other bacterial	<i>Escherichia coli</i> , group B <i>Streptococcus</i> , <i>Haemophilus influenzae</i> , <i>Klebsiella pneumoniae</i> ,	HAQ Index, proportion coverage by PCV3 vaccine, proportion coverage	Neonatal, Post-neonatal–5,

central nervous system infections	<i>Listeria monocytogenes</i> , <i>Neisseria meningitidis</i> , <i>Staphylococcus aureus</i> , <i>Streptococcus pneumoniae</i> , virus	by Hib3 vaccine, age group, proportion of population covered by '10-'15 MenAfriVac rollout ^{1,34}	5-50, 50-70, 70+
Peritoneal and intra-abdominal infections	<i>Citrobacter</i> spp., <i>Enterobacter</i> spp., <i>Enterococcus faecalis</i> , <i>Enterococcus faecium</i> , <i>Escherichia coli</i> , <i>Klebsiella pneumoniae</i> , other <i>Klebsiella</i> species, <i>Proteus</i> spp., <i>Pseudomonas aeruginosa</i> , <i>Serratia</i> spp., <i>Staphylococcus aureus</i>	HAQ Index, age group	Under 5, 5-50, 50-70, 70+
Bacterial infections of the skin and subcutaneous systems	<i>Acinetobacter baumannii</i> , <i>Enterobacter</i> spp., <i>Enterococcus faecalis</i> , other enterococci, <i>Escherichia coli</i> , group A <i>Streptococcus</i> , group B <i>Streptococcus</i> , <i>Klebsiella pneumoniae</i> , <i>Proteus</i> spp., <i>Pseudomonas aeruginosa</i> , <i>Staphylococcus aureus</i>	HAQ Index, age group	Under 5, 5-50, 50-70, 70+
Urinary tract infections and pyelonephritis	<i>Acinetobacter baumannii</i> , <i>Citrobacter</i> spp., <i>Enterobacter</i> spp., <i>Enterococcus faecalis</i> , <i>Enterococcus faecium</i> , other enterococci, <i>Escherichia coli</i> , group B <i>Streptococcus</i> , <i>Klebsiella pneumoniae</i> , <i>Morganella</i> spp., <i>Proteus</i> spp., <i>Providencia</i> spp., <i>Pseudomonas aeruginosa</i> , <i>Serratia</i> spp., <i>Staphylococcus aureus</i>	HAQ Index, age group, HAI/CAI	Under 5, 5-50, 50-70, 70+

731 Group A *Streptococcus* = *Streptococcus pyogenes*. Group B *Streptococcus* = *Streptococcus agalactiae*. HAQ Index = Healthcare Access and
 732 Quality Index. HAI/CAI = hospital-acquired infection/community-acquired infection. * Enterotoxigenic *Escherichia coli* (ETEC) and
 733 Enteropathogenic *Escherichia coli* (EPEC) are only reported for the diarrhea syndrome.

734 *Section 3.4.7: Exceptions and special handling*

735 There were several notable exceptions and special handling decisions made for each individual pathogen distribution
 736 model, which we hope to address with more sustainable approaches in our future work. For example, for cardiac
 737 infections, we used the pathogen distribution for bloodstream infections rather than estimating specific distributions
 738 for these syndromes, due to a lack of complete literature reviews on the aetiologies and case-fatality rates of these
 739 syndromes. We consider this to be a serious limitation of our methodology, but do not anticipate that is seriously
 740 impactful on our final estimates.

741 In diarrhoea patients, cultures of specimens taken from the gastrointestinal tract, bowels, rectum, or stool are almost
 742 always affected by contaminants or pathogens that are not the cause of diarrhoea. For this reason, we believe that
 743 our input data and modelling framework are not able to accurately capture the aetiologies of diarrhoea. We chose to
 744 use GBD estimates of the aetiologies of diarrhoea in deaths instead of running our own model.¹³ Nonetheless, a
 745 major limitation of using such approach is that the GBD diarrhoea aetiology estimates are population attributable
 746 fractions (PAFs) for each pathogen. These PAFs may add to greater than 1 and the authors made no attempt to
 747 quantify the extent of co-occurrence of pathogens; the latter is inconsistent with the pathogen distribution estimation
 748 method used in our study, which quantifies polymicrobial infections and estimates all pathogens as mono-infections.
 749 Hence, in order to avoid duplication of cases in our framework, we had to make some assumptions about the co-
 750 occurrence of pathogens in diarrhoea (details provided in the appendix of Murray et al.¹).

751 Certain skin and subcutaneous samples are easily affected by contaminants, colonization, and other pathogens that
 752 are not the cause of infection. For this reason, we considered microbial data and mortality surveillance to be too
 753 difficult to extract meaningful aetiology information from, and instead used only ICD-coded databases (multiple
 754 cause of death, hospital discharge, and linkage data) and literature studies as inputs into our model of the pathogen
 755 distribution of skin infections.

756 We dropped all data on *S. pneumoniae* for community-acquired LRI and thorax infections in non-neonatal age
 757 groups except our estimates from the vaccine probe analysis. Because dedicated anaerobic cultures were not
 758 routinely performed for peritoneal samples, we dropped all anaerobes observed in the data for and excluded
 759 anaerobes as an etiology of intra-abdominal infections. Moreover, due to the unique pattern of meningitis in
 760 neonates, particularly the high prevalence of GBS, we modeled neonatal and adult central nervous syndrome
 761 infections separately.

762 For three infectious syndromes, we did not run a pathogen distribution model – these are “Typhoid, paratyphoid, and
 763 invasive non-typhoidal *Salmonella*”, “Tuberculosis” and “Gonorrhoea and chlamydia” infectious syndromes. They
 764 are all caused by distinct pathogens whose individual burdens are already estimated in GBD as separate causes of

765 death. Therefore, for these syndromes, we simply used GBD estimates. MTB- or HIV-associated opportunistic
766 infections were not included as part of the infectious syndrome aetiology because they are classified as MTB and
767 HIV cases according to the GBD methodology.

768 *Section 3.4.8: Model validation*

769 To assess model validity, we calculated the root mean square error (RMSE) and coefficient of determination (R^2) for
770 each pathogen distribution model in proportion space for both in-sample and out-of-sample predictions. Proportions
771 were predicted for each observation using the specific denominator observed from that study. For example, if a
772 given study reported on only *E. coli* and *S. pneumoniae*, the predictions for model validation for this study were
773 calculated as proportions of the total for *E. coli* and *S. pneumoniae*. In order to calculate out-of-sample fit, we
774 perform non-exhaustive cross-validation, with each round of the validation holding out 1 country of data at a time.
775 This leave-one-country-out approach simulates the prediction task of estimating the pathogen distribution of a
776 country for which we have no data.

777 R^2 ranges from 0.784 to 0.867 in-sample and from 0.755 to 0.837 out of sample, indicating good model fit with only
778 modest losses when data are moved out of sample. RMSE ranges from 0.129 to 0.149 in-sample and from 0.141 to
779 0.159 out of sample. Given that the data are expected to vary from the model predictions according to the
780 observation-level variance, and the fact that the RMSEs are relatively consistent between in-sample and out-of-
781 sample, these RMSEs are reasonable. Overall, these metrics show that these models have good fit and good out-of-
782 sample predictive ability.

783 *Table 3.4.8.1: In-sample and out-of-sample validation metrics for pathogen distribution models (GLOBAL)*

Infectious syndrome	Model type	R^2		RMSE	
		In sample	Out of sample	In sample	Out of sample
Bacterial infections of the skin and subcutaneous systems		0.808	0.771	0.129	0.141
Bloodstream infections		0.822	0.785	0.128	0.141
Infections of bones, joints, and related organs		0.858	0.837	0.141	0.151
Lower respiratory infections and all related infections in the thorax		0.810	0.780	0.142	0.153
Meningitis and other bacterial central nervous system infections	Neonatal	0.858	0.803	0.134	0.158
	Non-neonatal	0.867	0.822	0.129	0.150
Peritoneal and intra-abdominal infections		0.815	0.812	0.147	0.148
Urinary tract infections and pyelonephritis		0.784	0.755	0.149	0.159

784 *Out of sample metrics calculated using leave-one-country-out cross validation*

785 **Section 4: Pathogen-specific ratios for GBD pathogen adjustment**

786 To make our estimates of burden comparable between all pathogens included in the paper, we developed pathogen-
787 specific ratios that incorporated the burden of immediate and intermediate causes of death from pathogens modeled
788 exclusively by the GBD. We used these ratios to adjust both deaths and years of life lost (YLLs). Adjusted YLLs
789 were then combined with years lived with disability (YLDs) to generate adjusted disability-adjusted life years
790 (DALYs). We generated ratios for the following pathogens:

- 791 • Hepatitis A
- 792 • Hepatitis B
- 793 • Hepatitis E
- 794 • Ascariasis
- 795 • Human papillomavirus
- 796 • Chagas disease
- 797 • Cystic echinococcosis

- 798 • Cysticercosis
 799 • Dengue
 800 • Diphtheria
 801 • HIV/AIDS
 802 • Malaria
 803 • Measles
 804 • *Neisseria gonorrhoeae*
 805 • Other neglected tropical diseases
 806 • Rabies
 807 • Schistosomiasis
 808 • Syphilis
 809 • Tetanus
 810 • Tuberculosis
 811 • Varicella and herpes zoster
 812 • Visceral leishmaniasis
 813 • *Bordetella* species (Whooping Cough)
 814 • Yellow fever

815 **Section 4.1: Generating the ratios**

816 To create these ratios, we used multiple cause of death (MCOD), hospital, linkage, and MITS data (Table 4.1.1) to
 817 determine the pathogen-specific fraction of deaths coming from immediate and intermediate causes of death, also
 818 known as the cause of death chain. Ratios were made only for pathogens with at least 200 recorded deaths in our
 819 dataset. The median number of deaths per pathogen in our data was 5,345 for all ages, 4,609 for the age group 5
 820 plus, and 981 for under 5. Next, we divided the total number of deaths where the pathogen was the underlying cause
 821 of death (α) by the total number of deaths where the pathogen was diagnosed anywhere in the cause of death chain
 822 (β) (Equation 4.1.1). A ratio of 1 indicated that no fatal burden was lost by considering only the underlying cause of
 823 death estimates provided by the GBD.

824
$$\frac{\alpha}{\beta} \text{ (Equation 4.1.1)}$$

825 We generated the ratios for the following age groups: under 5, over 5, and all ages. The means of a binomial
 826 distribution were used for the point estimates and the 95% UIs were delineated using the 2.5th and 97.5th percentiles
 827 of 1,000 draws. Uncertainty is attributable to sample size variability between data sources and data availability. The
 828 binomial distribution was defined by n, the number of times the cause appeared anywhere in the cause of death
 829 chain, including the underlying cause of death, and p, the probability of the cause being the underlying cause of
 830 death (Equation 4.1.2).

831
$$\frac{1}{Bin(n,p)} \text{ (Equation 4.1.2)}$$

832 Table 4.1.1. Input data to the pathogen-specific ratios

Country	Source	Years	Year Range	Deaths
Austria	Hospital	18	2001-2018	460,840

Bangladesh	MITS (from CHAMPS)	6	2017-2022	105
Brazil	Hospital	6	2015-2020	964,447
	MCOD	23	1999-2021	20,980,227
Canada	Hospital	16	1994-2009	45,191
Colombia	MCOD	24	1998-2021	4,711,423
Ethiopia	MITS (from CHAMPS)	3	2019-2021	71
Georgia	Hospital	7	2014-2020	34,612
India	Hospital	4	2014-2017	13,371
Italy	Hospital	17	2005-2021	3,695,034
	Linkage	16	2003-2018	112,371
	MCOD	18	2003-2020	10,605,540
Kenya	MITS (from CHAMPS)	6	2017-2022	267
Kyrgyzstan	Hospital	1	2012	9
Libya	Hospital	2	2019-2020	439
Mali	MITS (from CHAMPS)	5	2017-2021	93
Mexico	Hospital	21	2000-2020	833,344
	MCOD	8	2009-2016	4,324,274
Mongolia	Hospital	2	2019-2020	2
	MCOD	3	2018-2020	13,192
Mozambique	MITS (from CHAMPS)	6	2017-2022	331
New Zealand	Hospital	10	2011-2020	116,643
	Linkage	11	2000-2010	144,515
Pakistan	Hospital	3	2017-2019	4,214
Philippines	Claims	1	2016	75,664
Sierra Leone	MITS (from CHAMPS)	4	2019-2022	287
South Africa	MCOD	20	1997-2016	4,687,023
	MITS (from CHAMPS)	6	2017-2022	567
Taiwan (Province of China)	MCOD	10	2008-2017	1,185,682
United Arab Emirates	MCOD	5	2014-2018	64,380
United States of America	Hospital	31	1980-2010	7,940,360
	MCOD	41	1980-2020	77,287,402

833

834 Recorded deaths in Table 4.1.1. meet two criteria:

835 1. At least two unique causes of death and/or diagnoses are associated with the death records

836 2. The ICD-codes used to describe the causes of death and/or diagnoses have at least 2 digits of detailž

837 Here, we would also like to clarify the steps of our modelling procedure in which we relied on data from the fewest
 838 number of countries. These were 1) to estimate the proportion of each underlying cause of death associated with
 839 sepsis and specific infectious syndromes, and 2) the ratio indicating how commonly a diagnosed infectious cause

840 was implicated as an intermediate vs. underlying cause of death by the attending clinician. With respect to #1, we
841 use data from 16 countries, while for #2, we used data from 24 countries (including Mongolia, Pakistan, the
842 Philippines, and the United Arab Emirates).

843 **Section 4.2: Exceptions**

844 The following pathogens were not adjusted due to being recorded in fewer than 200 death records in our data:

- 845 • African trypanosomiasis
846 • *Salmonella* Paratyphi (Paratyphoid fever)
847 • Zika Virus

848 The following pathogens were adjusted using all age scalars for the under 5 age group due to having fewer than 200
849 death records in the under 5 age group:

- 850 • Chagas disease
851 • Cystic echinococcosis
852 • Cysticercosis
853 • Diphtheria
854 • Hepatitis B
855 • *Neisseria gonorrhoeae*
856 • Rabies
857 • Schistosomiasis
858 • Yellow fever

859 Acute hepatitis E was not adjusted in under 5 due to the rarity of this pathogen in this age group and cervical cancer
860 was not adjusted for under 5 due to the realistic age restrictions associated with this cause of death.

861 **Section 4.3: Ratios**

862 Table 4.3.1. pathogen-specific ratios

Pathogen	Age	Scalar (95% UI)
Yellow fever	Under 5	1.04 (1.02 - 1.06)
	5 plus	1.04 (1.02 - 1.06)
	All Ages	1.04 (1.02 - 1.06)
Cystic echinococcosis	Under 5	1.65 (1.55 - 1.75)
	5 plus	1.65 (1.55 - 1.75)
	All Ages	1.65 (1.55 - 1.75)
Hepatitis E	Under 5	1.0 (1.0 - 1.0)
	5 plus	1.74 (1.59 - 1.95)
	All Ages	1.75 (1.57 - 1.95)
Rabies	Under 5	1.15 (1.1 - 1.2)
	5 plus	1.14 (1.1 - 1.19)
	All Ages	1.15 (1.1 - 1.2)
Cysticercosis	Under 5	1.27 (1.25 - 1.29)
	5 plus	1.27 (1.25 - 1.28)
	All Ages	1.27 (1.25 - 1.29)
Human papillomavirus	5 plus	1.07 (1.07 - 1.08)
	All Ages	1.07 (1.07 - 1.08)
Schistosomiasis	Under 5	1.08 (1.07 - 1.09)

	5 plus	1.08 (1.07 - 1.08)
	All Ages	1.08 (1.07 - 1.09)
Chagas disease	Under 5	1.06 (1.05 - 1.06)
	5 plus	1.06 (1.05 - 1.06)
	All Ages	1.06 (1.05 - 1.06)
<i>Neisseria gonorrhoeae</i>	Under 5	1.67 (1.55 - 1.81)
	5 plus	1.66 (1.54 - 1.79)
	All Ages	1.67 (1.55 - 1.81)
Dengue	Under 5	1.03 (1.02 - 1.04)
	5 plus	1.09 (1.09 - 1.1)
	All Ages	1.09 (1.08 - 1.09)
Tetanus	Under 5	1.15 (1.1 - 1.21)
	5 plus	1.07 (1.06 - 1.08)
	All Ages	1.08 (1.07 - 1.08)
Hepatitis A	Under 5	1.07 (1.05 - 1.1)
	5 plus	1.63 (1.6 - 1.65)
	All Ages	1.58 (1.56 - 1.61)
Diphtheria	Under 5	2.29 (2.03 - 2.63)
	5 plus	2.68 (2.26 - 3.21)
	All Ages	2.29 (2.03 - 2.63)
Visceral leishmaniasis	Under 5	1.03 (1.02 - 1.04)
	5 plus	1.1 (1.09 - 1.12)
	All Ages	1.08 (1.08 - 1.09)
Hepatitis B	Under 5	1.32 (1.31 - 1.34)
	5 plus	1.32 (1.31 - 1.33)
	All Ages	1.32 (1.31 - 1.34)
Malaria	Under 5	1.18 (1.14 - 1.22)
	5 plus	1.13 (1.11 - 1.14)
	All Ages	1.13 (1.12 - 1.15)
Measles	Under 5	1.31 (1.24 - 1.38)
	5 plus	1.59 (1.47 - 1.72)
	All Ages	1.43 (1.37 - 1.5)
Other neglected tropical diseases	Under 5	1.28 (1.22 - 1.35)
	5 plus	1.33 (1.31 - 1.34)
	All Ages	1.32 (1.31 - 1.34)
Bordetella species (Whooping Cough)	5 plus	1.89 (1.68 - 2.13)
	Under 5	1.08 (1.06 - 1.09)
	All Ages	1.13 (1.11 - 1.15)
Ascariasis	Under 5	1.21 (1.17 - 1.25)
	5 plus	1.36 (1.29 - 1.43)
	All Ages	1.26 (1.23 - 1.3)

Varicella and herpes zoster	Under 5	1.17 (1.15 - 1.18)
	5 plus	2.45 (2.42 - 2.48)
	All Ages	2.26 (2.24 - 2.29)
Syphilis	Under 5	1.28 (1.26 - 1.3)
	5 plus	2.53 (2.48 - 2.59)
	All Ages	1.98 (1.95 - 2.0)
HIV/AIDS	Under 5	1.14 (1.13 - 1.14)
	5 plus	1.1 (1.1 - 1.1)
	All Ages	1.1 (1.1 - 1.1)
Tuberculosis	Under 5	1.39 (1.37 - 1.4)
	5 plus	1.43 (1.42 - 1.43)
	All Ages	1.43 (1.42 - 1.43)

863 **Section 5: *Helicobacter pylori* burden estimation:**

864 The burden for *Helicobacter pylori* was estimated based on GBD figures for stomach cancer, which were adjusted to
 865 represent total non-cardia stomach cancer, a form of stomach cancer for which *H. pylori* is thought to be the
 866 dominant cause. Fractions of stomach cancers that were non-cardia as compared to cardia were obtained from de
 867 Martel et al. 2020 which documented that 80.9% and 86.7% of gastric cancers for males and females, respectively,
 868 were non-cardia neoplasms.¹⁶ Based on the estimated fraction of gastric non-cardia cancers attributable to *H. pylori*
 869 from the same research (89%, 95%CI: 79-94), we then attributed a proportion of non-cardia-adjusted GBD stomach
 870 cancers to *H. pylori*. We incorporated the uncertainty for the estimated *H. pylori* attributable fraction by
 871 approximating a beta distribution with the same mean and 95% confidence bounds as those found in de Martel et al.
 872 2020, sampling 1,000 draws from that distribution, and ultimately multiplying those draws with GBD estimates.
 873 Limitations of this approach include the assumption that the proportion of non-cardia gastric cancer is consistent
 874 across the world, and the lack of attribution of burden of cardia cancers and non-Hodgkin gastric lymphomas to *H.*
 875 *pylori*.

876

885 **Supplementary Table 2: Source counts for 57 pathogens estimated by GBD 2019. Source counts are presented**
 886 **as nid, year, location, combinations.**

Cause name	Source Counts
Adenovirus	204
<i>Aeromonas</i> spp.	149
African trypanosomiasis	2944
Ascariasis	3395
Bordetella species (Pertussis)	11093
<i>Campylobacter</i> spp.	272
Chagas disease	2097
<i>Clostridium difficile</i>	107
Cryptosporidium	202
Cutaneous and mucocutaneous leishmaniasis	1056
Cystic echinococcosis	3532
Cysticercosis	3442
Dengue	5418
Diphtheria	3731
Ebola	51
<i>Entamoeba histolytica</i>	162
Enteropathogenic <i>Escherichia coli</i>	217
Enterotoxigenic <i>Escherichia coli</i>	234
Food-borne trematodiases	57
Genital herpes	338
Guinea worm disease	436
Hepatitis A	3053
Hepatitis B	468
Hepatitis C	332
Hepatitis E	2655
HIV/AIDS	5162
Hookworm disease	168
Human papillomavirus	7319
Influenza virus	370
Leprosy	1685
Lymphatic filariasis	561
Malaria	10803
Measles	12085
<i>Neisseria gonorrhoeae</i>	3985
Non-typhoidal Salmonella (diarrhea)	303
Norovirus	204
Onchocerciasis	351
other neglected tropical diseases	3651

Other unspecified infectious diseases	4261
Rabies	3527
Respiratory syncytial virus	312
Rotavirus	744
<i>Salmonella Paratyphi</i>	3422
Schistosomiasis	3923
<i>Shigella spp.</i>	276
Stomach cancer	3659
Syphilis	4913
Tetanus	3991
Trachoma	135
Trichomoniasis	137
Trichuriasis	156
Tuberculosis	4700
Varicella and herpes zoster	2874
<i>Vibrio cholerae</i>	3685
Visceral leishmaniasis	4521
Yellow fever	2777
Zika virus	485
Total	140790

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889 **Supplementary Table 3: Source counts for 28 pathogens estimated as part of the Global Research on**
 890 **Antimicrobial Resistance. Source counts are presented as number of isolates.**

Pathogen	Number of isolates
<i>Acinetobacter baumannii</i>	99,511
<i>Chlamydia</i> spp.	15,577
<i>Citrobacter</i> spp.	127,353
<i>Enterobacter</i> spp.	399,917
<i>Enterococcus faecalis</i>	940,348
<i>Enterococcus faecium</i>	524,379
<i>Escherichia coli</i>	7,783,843
Fungi	1,438,888
Group A <i>Streptococcus</i>	363,986
Group B <i>Streptococcus</i>	219,335
<i>Haemophilus influenzae</i>	96,938
<i>Klebsiella pneumoniae</i>	1,705,653
<i>Legionella</i> spp.	5,323
<i>Listeria monocytogenes</i>	16,300
<i>Morganella</i> spp.	124,288
<i>Mycoplasma</i> spp.	57,597
<i>Neisseria meningitidis</i>	37,641
Other <i>Enterococci</i>	37,191
Other <i>Klebsiella</i> species	166,774
Polymicrobial infections	4,435
<i>Proteus</i> spp.	670,723
<i>Providencia</i> spp.	35,773
<i>Pseudomonas aeruginosa</i>	1,252,431
<i>Salmonella Typhi</i>	16,450
<i>Serratia</i> spp.	106,321
<i>Staphylococcus aureus</i>	4,453,097
<i>Streptococcus pneumoniae</i>	982,319
Viral meningitis	170,568
Total	21,852,959

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892 **Supplementary Table 4: All-cause disability-adjusted life-years (DALYs) in counts and rates, for each GBD**
 893 **super-region, for all ages and under 5 years of age, both sexes, 2019 (Sources: GBD 2019 Diseases and**
 894 **Injuries Collaborators. Global burden of 369 diseases and injuries in 204 countries and territories, 1990–**
 895 **2019: a systematic analysis for the Global Burden of Disease Study 2019. Lancet 2020; 396: 1204–22;**
 896 <https://vizhub.healthdata.org/gbd-results/>

Location	Age	Metric	Mean Value	Upper	Lower
Sub-Saharan Africa	<5 years	Number	243891734.25	294668873.64	204720104.32
Sub-Saharan Africa	<5 years	Rate	147218.02	177868.14	123573.23
Sub-Saharan Africa	All ages	Number	510630214.28	584636593.89	450576878.91
Sub-Saharan Africa	All ages	Rate	47359.10	54222.92	41789.37
Latin America and Caribbean	<5 years	Number	18091597.29	22148493.34	14756413.94
Latin America and Caribbean	<5 years	Rate	37632.75	46071.60	30695.16
Latin America and Caribbean	All ages	Number	166067802.37	188607514.56	147230849.64
Latin America and Caribbean	All ages	Rate	28417.86	32274.91	25194.45
Southeast Asia, East Asia, and Oceania	<5 years	Number	39641447.77	45519251.39	34687635.62
Southeast Asia, East Asia, and Oceania	<5 years	Rate	28219.73	32403.98	24693.23
Southeast Asia, East Asia, and Oceania	All ages	Number	601252753.03	673101421.46	532376316.00
Southeast Asia, East Asia, and Oceania	All ages	Rate	27845.29	31172.75	24655.48
Central Europe, Eastern Europe, and Central Asia	<5 years	Number	6260246.00	7260055.57	5423229.43
Central Europe, Eastern Europe, and Central Asia	<5 years	Rate	22714.08	26341.70	19677.13
Central Europe, Eastern Europe, and Central Asia	All ages	Number	157814480.72	175327139.48	142714306.01
Central Europe, Eastern Europe, and Central Asia	All ages	Rate	37779.50	41971.89	34164.64
High-income	<5 years	Number	6409828.87	7180077.32	5721419.37
High-income	<5 years	Rate	11256.79	12609.48	10047.82
High-income	All ages	Number	323732733.12	368067442.92	284120170.63
High-income	All ages	Rate	29865.30	33955.31	26210.93
North Africa and Middle East	<5 years	Number	28813099.05	33501933.66	24842579.83
North Africa and Middle East	<5 years	Rate	48247.07	56098.45	41598.50
North Africa and Middle East	All ages	Number	163781896.54	186172200.68	143723029.83
North Africa and Middle East	All ages	Rate	26906.23	30584.53	23610.94
South Asia	<5 years	Number	127858088.49	150677267.16	108963941.03
South Asia	<5 years	Rate	77770.45	91650.35	66277.97
South Asia	All ages	Number	614740190.59	688694087.90	547579224.87
South Asia	All ages	Rate	34053.85	38150.56	30333.43
Global	<5 years	Number	470966042.00	557758708.00	402932837.00
Global	<5 years	Rate	71052.46	84146.47	60788.61
Global	All ages	Number	2538020071.00	2810205655.00	2285262551.00
Global	All ages	Rate	32801.70	36319.46	29535.03

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Supplementary Table 5: Pathogen-associated disability-adjusted life-years (DALYs) counts + 95% UIs, for each super-region, all ages in 2019

Location name	DALYs Count Mean							DALYs Count Lower							DALYs Count Upper							
	Central Europe, Eastern Europe, and Central Asia	High - income	Latin America and Caribbean	North Africa and Middle East	South Asia	South East Asia, East Asia, and Oceania	Sub-Saharan Africa	Central Europe, Eastern Europe, and Central Asia	High - income	Latin America and Caribbean	North Africa and Middle East	South Asia	South East Asia, East Asia, and Oceania	Sub-Saharan Africa	Central Europe, Eastern Europe, and Central Asia	High - income	Latin America and Caribbean	North Africa and Middle East	South Asia	South East Asia, East Asia, and Oceania	Sub-Saharan Africa	
<i>Acinetobacter baumannii</i>	4214 79.0 1	7784 65.7 1	8550 77.9 9	9751 80.9 5	5025 644.5 2	4333 959.0 8	4305 684.8 3	2490 30.5 2	4591 45.7 8	5302 41.6 9	5946 79.0 1	3294 190. 13	2600 672.7 2	2959 53.7 8	6684 1226 12	1282 805. 36	1490 808. 84	7373 785.4 0	6577 234.7 2	6130 184.1 4		
<i>Adenovirus</i>	1037 7.30	3066 2.73	7081 2.62	1954 53.6	1367 377.4	1807 42.26 1	4101 554.7 3	5647 .14	1701 7.84	3911 9.21	8661 7.16	7552 89.32	1014 64.5 1	2147 760.4 6	1831 7.06	4973 1.81	1311 36.8 5	4110 60.8 8	2353 067.8 9	3185 94.69 7		
<i>Aeromonas spp.</i>	5991 .11	2071 .10	1529 2.02	5590 7.67	4788 81.82	4297 4.28	9917 66.69	2785 .63	949. 49	7137 .05	2052 8.82	2188 83.94	1798 9.10	3980 28.28	1059 7.61	3601 .81	2902 8.44	1172 79.4 4	8599 64.57	8255 6.36	1921 581.1 1	
<i>African trypanosomiasis</i>	0.00	0.00	0.00	0.00	0.00	0.00	8261 5.46	0.00	0.00	0.00	0.00	0.00	0.00	3763 6.49	0.00	0.00	0.00	0.00	0.00	0.00	1557 91.81	
<i>Ascarasis</i>	787. 84	267. 80	3675 6.07	2454 2.04	3725 17.65	9093 1.70	2680 88.22	461. 72	157. 03	2203 8.84	1528 6.04	2116 74.63	5434 4.01	1973 64.65	1286 .92	441. 26	5981 3.41	3778 6.62	6193 26.67	1455 58.79	3558 66.75	
<i>Bordetella spp. (Pertussis)</i>	3333 7.64	1196 5.57	2034 75.7	7350 2.3	2584 82.2	1004 988.9	6934 900.7	1314 772.0	7992 .95	9220 1.38	2751 65.9	6642 10.00	4151 62.2	2822 826.3	6968 1.43	1751 7.96	3975 74.3	1576 850.	5946 30	2008 7	1375 119.3	5209. 0
<i>Campylobacter spp.</i>	5704 9.93	7461 3.67	1349 96.8	7760 6	2510 9.59	3035 234.1	3112 23.63	495.3 0	1616 2.90	1705 9.21	5018 0.95	2521 9.36	9669 69.62	9656 4.29	1193 850.6	1271 4	1662 76.5	2765 27.3	1810 9	5153 1	7319 34.58	6397 623.3
<i>Chagas disease</i>	0.00	3033 8.96	2570 22.9	0.00	0.00	0.00	0.00	0.00	2000 1.63	1701 89.1	0.00	0.00	0.00	0.00	0.00	7104 9.05	4221 71.1	0.00	0.00	0.00	0.00	
<i>Chlamydialia spp.</i>	9199 3.92	9584 6.16	1794 93.1	2901 2	1828 33.8	5312 331.7	2559 145.3	7529 9.25	7699 2.83	1377 82.9	2132 5	1392 96.6	4044 275.1	1988 62.9	1134 3	1214 62.4	2332 66.5	3829 61.3	2338 9	6869 12.71	3311 591.0	
<i>Citrobacter spp.</i>	9828 0.82	1159 62.2	1153 1	1107 0	5867 3	4633 67.93	4537 34.00	5239 7.19	7368 8.37	7392 9.14	6333 0.68	3508 32.37	2723 92.0	2735 96.81	1705 3	1728 50.0	1692 46.6	1747 2	8990 8	7235 46.31	6962 81.72	22.55

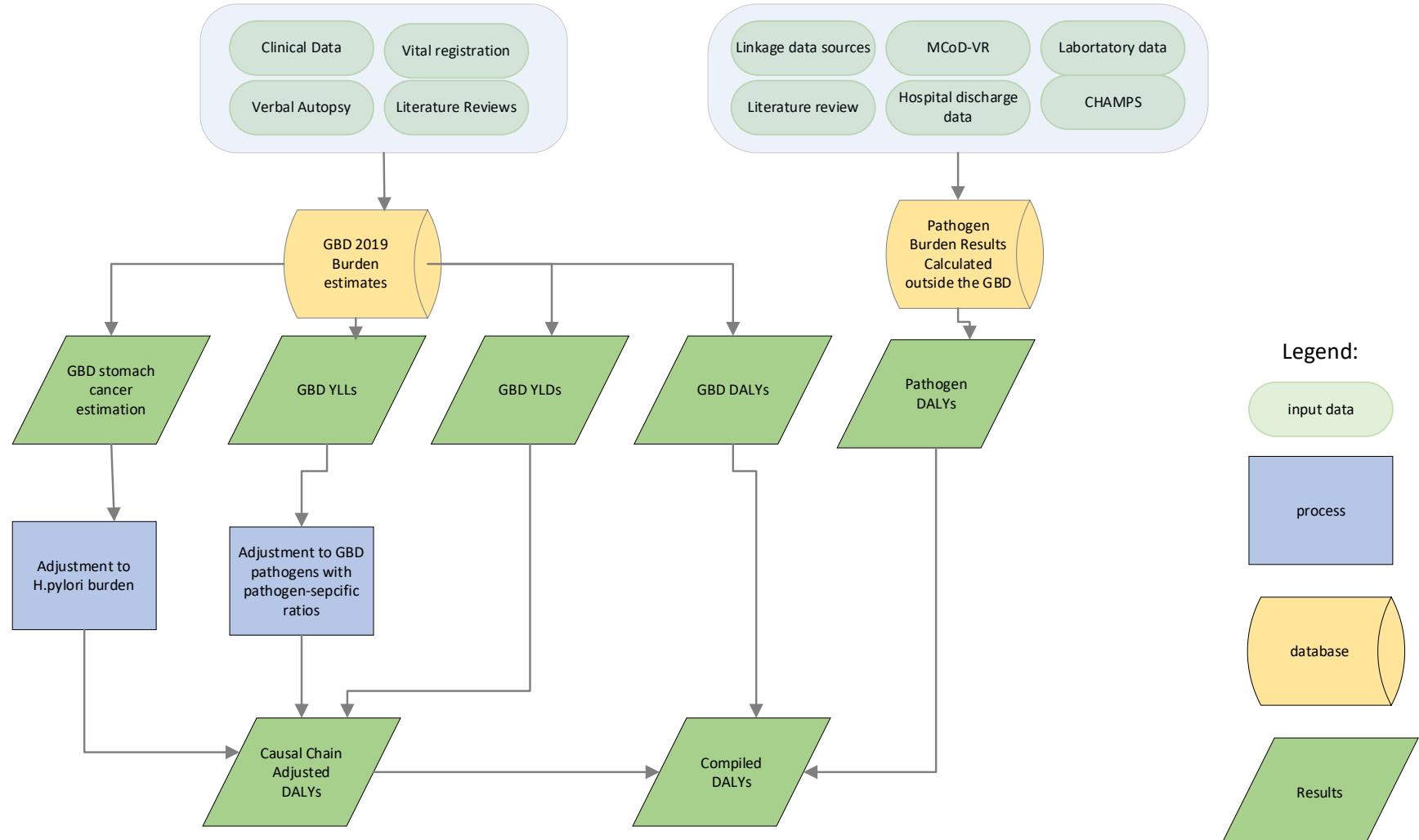
herpes zoster																					
Vibrio cholera e	1278 3.248	0	3808 1.955	3616 67.48	2436 99.52	1026 6	2657 52.36	6423. 945	0	1684 9.851	1591 89.66	1157 3	5207 46.30	1187 73.1	2426 1.416	0	7649 5.582	7562 13.25	4403 9	1877 30.95	4822 29.58
Viral mening itis	4327. 56	3710. 221	1617 3.692	3517 0.707	1460 50.65	4221 1.996	5925 51.24	2819. 111	2508 .817	1029 9.168	1738 4.583	1019 68.05	2985 2.784	3800 88.79	6642. 918	5176. 603	2359 0.908	7151 1.014	2103 40.44	5958 3.263	8767 62.83
Visceral leishmaniasis	852.3 86	211.7 45	1768 5.144	1012 9.854	2591 8.44	23.64 2	8391 8.71	1.509	0.62 2	24.96 8	19.67 6	35.25	2.457	4260 4.646	8200. 013	2019. 734	7055 8.873	9359 9.727	1443 72.89	100.0 85	1377 43.52
Yellow fever	0	232.9 97	414.4 38	2249. 79	0	0	4112 8.799	0	18.5 22	108.7 98	242.0 84	0	0	1444 5.355	0	1064. 269	1144. 428	9122. 165	0	0	9056 0.807
Zika virus	0	2.413	105.0 55	0	0	0	11.13 2	0	0.74 3	62.03 7	0	0	0	2.444	0	5.929	174.4 27	0	0	0	30.71 7
TOTAL	2366 522.2	1060 167.6	7702 197.8	1356 3138.	7127 0512.	1914 3384.	1933 4132	1896 953.9	7543 25.5	5702 475.8	1039 6241.	5577 1055.	1542 7699.	1578 4912	2991 580.9	1457 356.0	1013 9173.	1724 69	9008 4786.	2331 0106.	2370 9033.
	58 37		72	78	65	13	0.2	72	04	92	69	06	04	8.8	73	95	69	47	31	95	5.2

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914 Section 7: Estimation Flowchart



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917 **Section 8: GATHER Compliance: Guidelines for Accurate and Transparent Health**
 918 **Estimates Reporting**

919 This study complies with GATHER recommendations. We have documented the steps in our analytical procedures
 920 and detailed the data sources used. The GATHER recommendations can be found on the GATHER website.



Checklist of information that should be included in new reports of global health estimates

Item #	Checklist item	Reported location
Objectives and funding		
1	Define the indicator(s), populations (including age, sex, and geographic entities), and time period(s) for which estimates were made.	This can be found in the methods section of the main text.
2	List the funding sources for the work.	This can be found in the Funding Section of the main text.
Data Inputs		
For all data inputs from multiple sources that are synthesized as part of the study:		
3	Describe how the data were identified and how the data were accessed.	This can be found in the Overview and Sources of Information and in the data sources in the appendix.
4	Specify the inclusion and exclusion criteria. Identify all ad-hoc exclusions.	This is relevant to some literature studies and can be found in the appendix.
5	Provide information on all included data sources and their main characteristics. For each data source used, report reference information or contact name/institution, population represented, data collection method, year(s) of data collection, sex and age range, diagnostic criteria or measurement method, and sample size, as relevant.	The full list of data sources is available here . The estimates from the GBD study can be found in the GBD results tool and the AMR estimates can be found here .
6	Identify and describe any categories of input data that have potentially important biases (e.g., based on characteristics listed in item 5).	Data limitations can be found in the Limitations section of the main text.
For data inputs that contribute to the analysis but were not synthesized as part of the study:		
7	Describe and give sources for any other data inputs.	The published estimates can be found in the GHDx .
For all data inputs:		
8	Provide all data inputs in a file format from which data can be efficiently extracted (e.g., a spreadsheet rather than a PDF), including all relevant meta-data listed in item 5. For any data inputs that cannot be shared because of ethical or legal reasons, such as third-party ownership, provide a contact name or the name of the institution that retains the right to the data.	The results of this study and the input data citations can be found in the GHDx .
Data analysis		
9	Provide a conceptual overview of the data analysis method. A diagram may be helpful.	This can be found in the methods section.
10	Provide a detailed description of all steps of the analysis, including mathematical formulae. This description should cover, as relevant, data cleaning, data pre-processing, data adjustments and weighting of data sources, and mathematical or statistical model(s).	This can be found in the methods section.
11	Describe how candidate models were evaluated and how the final model(s) were selected.	This can be found in the methods appendix in the section for pathogen distribution. The results pulled from the GBD have been extensively published previously.

12	Provide the results of an evaluation of model performance, if done, as well as the results of any relevant sensitivity analysis.	This can be found in the methods appendix for pathogen distribution, infectious syndrome, case fatality rate.
13	Describe methods for calculating uncertainty of the estimates. State which sources of uncertainty were, and were not, accounted for in the uncertainty analysis.	This can be found in the methods appendix in each modelling component section.
14	State how analytic or statistical source code used to generate estimates can be accessed.	Published code is available on github
Results and Discussion		
15	Provide published estimates in a file format from which data can be efficiently extracted.	The published estimates can be found in the GHDx .
16	Report a quantitative measure of the uncertainty of the estimates (e.g. uncertainty intervals).	All estimates reported have uncertainty intervals.
17	Interpret results in light of existing evidence. If updating a previous set of estimates, describe the reasons for changes in estimates.	The research in context section explains these results in light of existing evidence.
18	Discuss limitations of the estimates. Include a discussion of any modelling assumptions or data limitations that affect interpretation of the estimates.	The limitations section of the main text describes data and modeling limitations.

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927 **Section 9: References**

- 928 1 Antimicrobial Resistance Collaborators. Global burden of bacterial antimicrobial resistance in 2019: a systematic
929 analysis. *The Lancet* 2022; **399**: 629–55.
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933 territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet* 2020;
934 **396**: 1204–22.
- 935 4 GBD 2019 Demographics Collaborators. Global age-sex-specific fertility, mortality, healthy life expectancy
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