## Background Information

### Importance of data for maternal mortality

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### Data Sources Used to Estimate Maternal Mortality

The maternal mortality ratio (MMR) is typically estimated from one or more of a diverse range of data sources. More specifically, MMR estimates are typically informed by national civil registration and vital statistics (CRVS) systems, which are country-specific data collection systems that record births and medically certified deaths within a country, with deaths associated with the cause of death in line with the International statistical classification of diseases and related health problems (ICD) [1, 2]. MMR estimates are also informed by specialised studies on maternal mortality, whose goal is to determine the true MMR within a specific geographic region. These studies use data from information sources like police and medical records, national registries, administrative reviews, medical autopsies, and censuses [1]. In addition to specialised studies, the MMR can also be informed by broader surveys, censuses, and national surveillance data, which include both national surveys and Multiple Indicator Cluster Surveys (MICS), which use the sisterhood method to better understand the incidence of maternal deaths in a population [1]. However, despite this diverse range of data sources, it is difficult to estimate accurate MMR values due to missing data and/or errors in the collected data [2].

1. Citation: Trends in maternal mortality estimates 2000 to 2023: estimates by WHO, UNICEF, UNFPA, World Bank Group and UNDESA/Population Division. Geneva: World Health Organization; 2025. Licence: CC BY-NC-SA 3.0 IGO
2. <https://www.tandfonline.com/doi/epdf/10.1080/2330443X.2023.2286313?needAccess=true>

## Literature Review

### Existing Methods for Estimating the MMR

#### The United National Maternal Mortality Estimation Inter-Agency Group (MMEIG) Estimates

The MMEIG is a collaboration between United Nations Member States, the WHO, the World Bank Group, the United National Population Fund (UNFPA), the United National Agency for Children (UNICEF), and the United National Department of Economic and Social Affairs, Population Division (UNDESA/Population Division). This collaboration produces estimates of regional and country-specific maternal mortality rates (MMR) between 2000 and 2023 for women between the ages of 15 and 49 [1]. The group has published multiple reports at different intervals in this time frame, with each report adding MMR estimates for country-years elapsed since the previous report and, in some cases, updating the model used to estimate the MMR [1].

The MMEIG considers data from a variety of sources to produce these MMR estimates. More specifically, it uses data from Member States’ civil registration and vital statistics (CRVS) systems, as well as information from specialised maternal mortality studies, surveys, censuses, and national surveillance data, as described in the background information. Observations from sources other than CRVS systems and specialised studies were increased by 10% to account for underreporting due to deaths occurring early in pregnancy that may have been missed. Additionally, the MMEIG uses data from other United National agencies as inputs and covariates in its MMR model [1]. For example, the MMEIG sourced estimates of all-cause deaths among women aged 15 to 49, live births, total fertility and age-specific fertility rates, gross domestic product (GDP), skilled birth attendance rates, and deaths due to HIV from other agencies.

The MMEIG’s current MMR estimates are produced by a combination of two models. First, the Bayesian maternal mortality misclassification (BMis) model calculates adjustment factors for the provided CRVS data to account for under-reporting of maternal deaths and reporting errors [1,3]. These reporting errors are due to either incorrect medical classification of cause of death or incorrect application in applying the correct ICD code [1, 3]. Errors in CRVS data were defined in terms of sensitivity (probability of correctly classifying a maternal death) and specificity (probability of correctly classifying non-maternal deaths). Global and country-specific adjustment factors were calculated using specialised studies, as specialised studies are considered ‘gold-standard data’, and can thus provide a benchmark for the accuracy of CRVS data [3]. Previous studies have found that the level of misclassification in CRVS systems compared to specialised studies is typically around 50% [2]. Given that 53% of the total data input into the MMEIG’s maternal mortality estimate model comprised of CRVS data, these adjustment factors are essential to being able to accurately predict MMR [3]. Global estimates were calculated by fitting the BMis model to specialised study data from all countries and were used to determine the adjustment factors for countries with no specialised studies [3]. For countries with at least specialised study, the BMis model is fit to country-specific data, but with hyperparameters from the global model [3].

After using the BMis model to adjust the CRVS for errors, the MMEIG estimates the MMR per country per year using the Bayesian maternal mortality estimation (BMat) model [1]. In the latest iteration of the BMat model, the MMEIG estimates MMR for WHO Member States with populations of at least 100,000 people [3]. The BMat calculates MMR as the sum of non-HIV-related maternal deaths and HIV-related maternal deaths, where death was due to pregnancy-induced aggravation on the existing HIV/AIDS condition [1]. To reduce errors caused by under-reporting of all-cause deaths, the model first calculated the proportion of maternal deaths among all-cause deaths, then converted this measurement into the MMR [2].

The BMat estimates non-HIV-related MMR using a Bayesian hierarchical regression model [3]. The model’s covariates are GDP per capita, general fertility rate, and presence of a skilled birth attendant. These covariates were representatives of three broad predictive groups: social and economic development (GDP), process (skilled care), and risk exposure (fertility) variables [1]. The expected non-HIV MMR was then multiplied by a data-driven multiplier, which adjusted the expected non-HIV MMR based on how closely the data indicated that the non-HIV MMR tracked with the covariates. For example, if the data indicates that the non-HIV MMR decreased more slowly than predicted by the covariates alone, the data-driven multiplier would reduce the MMR estimate [1]. The multiplier was estimated using an autoregressive ARIMA process [3]. The less data available for a specific country-year, the more strongly the covariates affect the non-HIV MMR estimate and the less strongly the effect of the data-driven multiplier [1]. This inclusion of a data-driven multiplier was a relatively new addition to the model, with versions of the model used before 2014 not including the multiplier [2]. The use of the data-driven multiplier was motivated by criticism that the earlier models which solely based their MMR predictions on country-specific covariates did not always echo country-level trends in maternal mortality, which were important reflections of a country’s progress toward meeting the Millenium Development Goals [2].

While the model was fit to all data provided by the country, it placed higher weight on values with lower error variances, which were derived from calculating the random error in the data collection processes. As a result of incorporating error, the final BMat estimates had smaller uncertainty intervals for countries with higher-quality data [1].

HIV-related MMR was estimated separately, as evidence indicates that HIV/AIDS is a prominent cause of maternal mortality in countries with ongoing HIV/AID epidemics, with studies showing that women infected with HIV have approximately 8 times higher risk of pregnancy-related death [1]. The HIV-related MMR estimate was calculated using data about the proportion of maternal and pregnancy-related deaths caused by HIV [2]. This calculation relies on a constant that defines the relative risk of dying from HIV/AIDS for a pregnant versus non-pregnant women, which is estimated in conjunction with experts and thus is semi-subjective [1,2].

The MMR estimates produced by the MMEIG also included maternal deaths that occurred between 2019 and 2023 due to the COVID pandemic [1].

#### The Global Burdan of Disease Estimates

Coordinated by the Institute of Health Metrics and Evaluation (IHME), the Global Burden of Disease Study (GBD) is an international scientific initiative that benchmarks major diseases, risk factors, and clinical intermediate outcomes [5]. The GBD uses a standardised approach to be able to compare its estimates across time, geographic populations, and health conditions [5]. GBD studies have been ongoing since 1993, with the estimates being reviewed by independent experts as well as the WHO Headquarters and Regional Offices [5]. Additionally, many of the studies have been published in prestigious journals like *Lancet* after being subject to peer-review cycles [5]. The GBD Studies’ strong reputation is apparent in their use in national planning by a variety of governments, such as the United Kingdom, Norway, and China [5].

The 2021 GBD Study produced estimates of maternal mortality for 204 countries between 1990 and 2021 using data from a diverse range of sources, including CRVS, verbal autopsy, sibling histories, surveillance, survey and census data, as well as police records and open-source databases [6]. The data is then cleaned, standardised, and any deaths reported with an unclear or incorrect cause-of-death are redistributed to a more likely cause of death [8]. This redistribution is performed by first assigning the garbage codes to a group of possible underlying causes of death. The garbage-coded deaths are then probabilistically redistributed among these different causes [8]. Data quality is quantified by a star rating system, where higher star estimates are associated with more complete, available data with a smaller presence of garbage codes [8].

The GBD Study estimated maternal mortality using cause of death ensemble modelling (CODEm) [4]. This involves generating multiple statistical models to capture the large number of factors that can co-vary with maternal mortality [4]. CODEm uses linear mixed effects regression (LMER) and spatiotemporal Gaussian process regression (ST-GPR) models, unlike the MMEIG estimates, which instead rely on Bayesian hierarchical regression [4]. Each of the models are used to test candidate covariates to maternal mortality, with each combination of covariates tested for plausibility based on the literature as well as statistical significance [4]. The candidate covariates are split into three groups depending on the level of evidence in the literature that supports a causal relationship between the covariate and the mortality measure [7]. Level 1 covariates have a strong causal relationship based on the biological disease process, while level 2 covariates have strong supporting evidence but no direct biological relationship [7]. Level 3 covariates have weak evidence supporting a causal relationship with the mortality measure [7].

The GBD 2021 Study used more covariates than the MMEIG, with the former using 19 covariates while the latter only used 3 (GDP, skilled birth attendance, and general fertility rate) [4, 1]. More specifically, the GBD study estimated maternal mortality using covariates including, but not limited to, age-specific fertility, maternal education, neonatal mortality ratio, skilled birth attendance, age-specific HIV mortality in females 10 to 54 years old, and age-standardised wasting [4]. Models based on this best set of covariates were then generated and tested on out-of-sample data [4].

The models’ weights in the ensemble were determined by their out-of-sample predictive performance [4]. The final mortality prediction is the mean of 1000 ensemble predictions, with each prediction being generated by one individual, component model. The likelihood of each model being chosen is determined by its weight [4]. The 1000 draws also allow the construction of a 95% uncertainty interval [4].

#### The Global Maternal Health Microsimulation Model (GMatH) Estimates

As opposed to the MMEIG and GBD models that use aggregate measures to estimate country-level maternal mortality statistics, the GMatH model simulates individual women’s reproductive lifecycles to determine estimates of maternal mortality [9]. More specifically, the model uses monthly cycles to simulate each stage of pregnancy to determine the incidence of complications related to pregnancy and childbirth [9]. As part of this simulation, the model must estimate the probabilities of pregnancy, termination, and complications as a result of individual-level and institutional risk factors [9].

Parameters governing transition probabilities to different states within the model were estimated from probability distributions based on empirical data where possible, and on expert opinion where data was unavailable [9]. Relationships between parameters were similarly derived through a mixture of empirical data and expert opinion [9]. The uncertainty in the models’ inputs was captured setting the parameters’ prior probability distributions based on a 5-level hierarchical model. The model was then fit to empirical data [9]. This empirical data was sourced from UN agencies, randomized clinical trials, observational studies, census data, survey data, expert opinion, and meta-analyses [9].

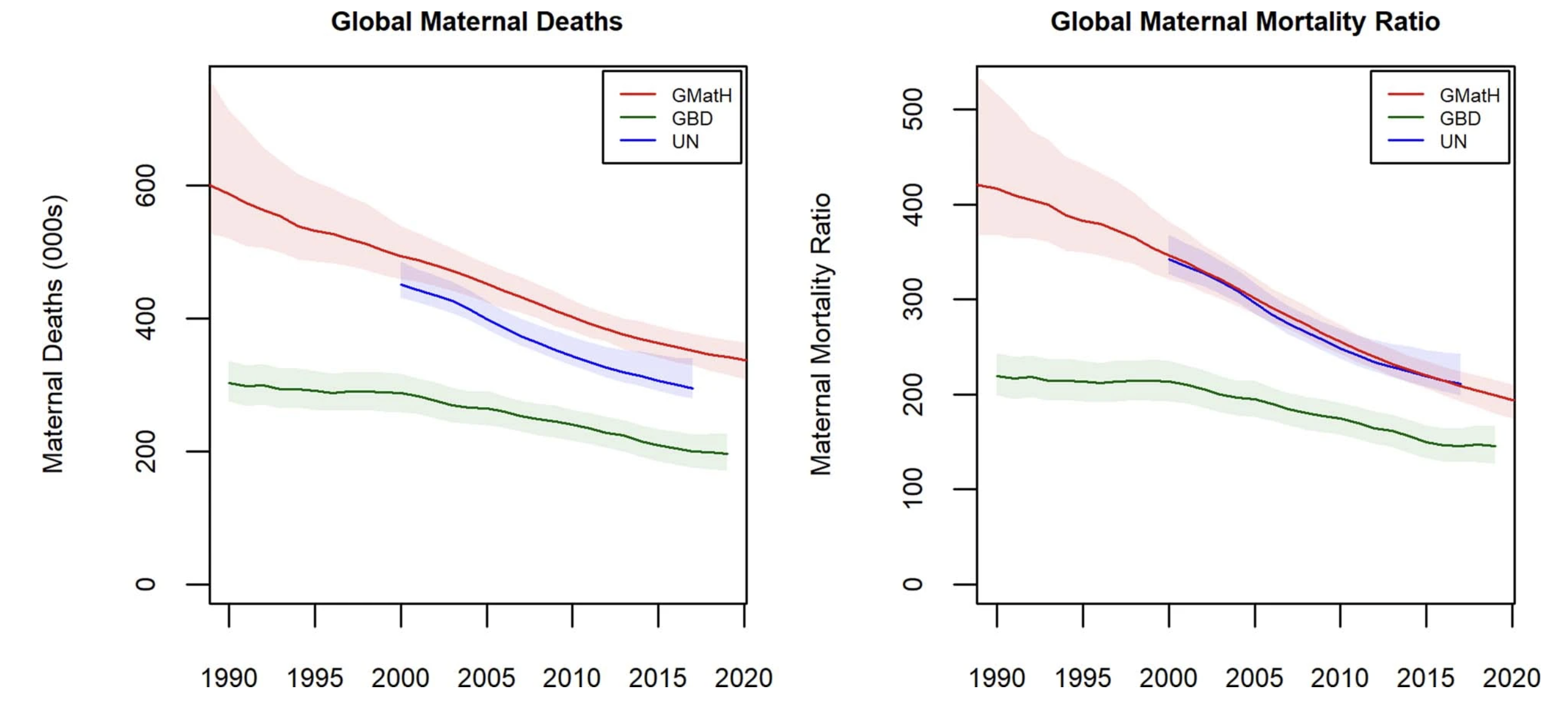
The model used 5 sets of parameters, categorised into biological parameters, family planning parameters, health system parameters, obstetrical complications, and clinical interventions [9]. Examples of biological parameters include age-specific probability of pregnancy, anaemia status, and risk of miscarriage, while examples of family planning parameters include contraceptive preferences. Health system parameters include the type of care available at birth, the probability of recognition of complications, and underreporting of maternal deaths. Examples of parameters that capture obstetrical complications are the risk of postpartum haemorrhage and risk of indirect obstetric causes, such as deaths due to HIV aggravated by pregnancy. Finally, examples of the parameters representing clinical interventions are the efficacy and availability of interventions for certain complications, such as hypertension management, as well as use of elective interventions, such as caesarean sections [9].

Through this process, the GMatH has been used to estimate annual values for maternal mortality indicators like cause-specific and total maternal deaths, MMR, live births, and the lifetime risk of maternal death [9]. These estimates were produced for 200 countries and territories between 1990 and 2050. Additionally, the calibrated model was used to make projections for each year up to 2050 [9].

To test the model’s predictive accuracy, the authors calibrated the model’s maternal death estimates using CRVS data collected between 1990 and 2015, then compared the model’s estimates for 2016 to 2020 to the CRVS estimates for the same time period. The mean absolute error for the total number of maternal deaths in test set was 47.5.

#### Comparison of the MMEIG, GBD, and GMatH Maternal Mortality Estimates

The authors of the original paper describing the GMatH model compare their model’s maternal mortality estimates to the latest estimates produced by the UN’s MMEIG and the GBD Study. The authors found substantial country-level differences in the estimates produced by the three models, with the GMatH global estimates being similar to the MMEIG’s global estimates but notably higher than the GBD’s global estimates [9]. These global differences were shown in the figure below. The deviations in the models’ estimates could result in the development of differing policies depending on which model is used as evidence for the policy [9].



<https://www.nature.com/articles/s41591-023-02310-x/figures/3>

Given these differences, the authors of the GMatH model describes their hope that their intrinsically different modelling approach could provide insight into the reason why the models results have diverged [9]. This also motivates my proposal for the use of a machine learning based approach, which may shed further light on this problem. The machine learning approach is further motivated in the next few sections.

#### Limitations of the MMEIG, GBD, and GMatH Models

The authors of the GMatH model motivated their model by describing how the models produced by the MMEIG and GBD Study may inadequately describe country-specific trends [9]. More specifically, they described how the MMEIG and GBD estimates were based on statistical relationships between aggregate country-level factors and MMR, preventing them from modelling variation within a specific country [9]. In contrast, the GMatH estimates maternal mortality outcomes using microsimulations of individual women’s reproductive lifecycles, with parameters reflecting heterogeneity across the country, thus allowing the model to better represent country-specific variation [9]. Additionally, while the MMEIG and GBD models operate based on correlations between their covariates and the maternal mortality outcome being estimated, the GMatH estimates maternal mortality using causal relationships between risks and the stage of a woman’s reproductive lifecycle, with the GMatH model incorporating substantially more parameters than used in the MMEIG or GBD models [9]. Consequently, the GMatH model can produce more robust predictions based on causal-inference. By incorporating these causal relationships, the GMatH model can be used by policymakers to explore possible policies targeting maternal health [9]. Additionally, the breadth of parameters used by the GMatH model allows a wider variety of policies to be modelled and health system barriers to be explored [9]. For instance, the GMatH model has been used to estimate the difference between maternal mortality outcomes for women from rural versus urban backgrounds, as well as for women with different levels of education [10]. Through this analysis, the study authors found that, in 2022, the global MMRs for women with a low, middle, and high education level were 536, 143, and 85, respectively [10]. Thus, the authors identified the importance of addressing women’s education as an avenue for improving maternal mortality outcomes [10]. In contrast, it is difficult to produce an effective policy to reduce maternal mortality based on the observation that the MMEIG’s maternal mortality outcomes are primarily predicted by GDP, which is a difficult outcome for politicians to change [9].

However, as described by the GMatH authors, the model is computationally intensive, as all parameters must be estimated and the model must be calibrated [9]. This computational complexity can be observed across all three models, as they each require significant calibration and data processing as well as input from a variety of sources. The MMEIG’s outputs are the result of collaboration between multiple UN agencies as well as consultation between the group and representatives from each Member State [1]. The GBD estimates are similarly developed with a wide variety of collaborators, with the GBD 2021 estimates for different mortality indicators produced, reviewed, and analysed by a network of over 11,000 collaborators [6]. The GMatH model was similarly developed using consultation with experts as well as significant training and calibration [9].

This computation effort is compounded by the need to not only develop the sophisticated statistical models, but also to transform low quality data into a usable form and embed uncertainty in the data from different sources. As described above, the MMEIG produced an extra model for the sole purpose of adjusting the CRVS data to account for mistakes while the GBD estimates were produced after categorising data quality using a star-based system and implementing complex algorithms to re-label unspecific or incorrect causes of death within the input data [2, 4, 8]. The GMatH model introduced separate parameters solely to model site-specific underreporting of maternal deaths, and the authors noted that a limitation of their method was lack of data about the extent of uncertainty in surveys [9].

Additionally, the models had to decide on parameters, another computationally intensive endeavour relying on a mixture of iterative experimentation, empirical data, and expert opinion. This task was complicated by the need to consider multicollinearity given the nature of statistical models particularly versus just letting a decision tree weed out unimportant ones

Moreover, the three models suffer from a lack of data, especially from lower income countries [1, 6, 9]. Given that all models rely on expert opinion to describe anticipated relationships between candidate covariates and maternal mortality outcomes, they are exposed to potential subjectivity, especially if experts from a subset of countries are queried about country-specific trends. For example, lack of data meant that some parameters used in GMatH model were not predicted by informative priors [9]. Since the subgroups with the most missing data are likely to be the lowest-income, the parameter values chosen to represent these subgroups may be misrepresentative.

### Statistical Models versus Machine Learning Models

Given these limitations, I propose the use of a machine learning based approach to estimate maternal mortality, as motivated by the following comparison between statistical models and machine learning technologies.

The models above rely to some extent on inference, where they create a mathematical model of the data generation process

* Identified covariates versus patterns used in ml that may also be useful (especially as unaffected by multicollinearity, which makes it difficult to isolate relationships between covariates and target variable)
* Give within-country as well due to diversity of features used
* No assumptions of parameter values used
  + All finetuned

More variables (10 below)

In addition, although previous analyses have focused on [health system](https://www.sciencedirect.com/topics/medicine-and-dentistry/health-system) and clinical interventions that can improve maternal health,[11](https://www.sciencedirect.com/science/article/pii/S2589537024002323" \l "bib11), [12](https://www.sciencedirect.com/science/article/pii/S2589537024002323" \l "bib12), [13](https://www.sciencedirect.com/science/article/pii/S2589537024002323" \l "bib13) fewer studies have explicitly examined the impact of [social determinants of health](https://www.sciencedirect.com/topics/medicine-and-dentistry/social-determinants-of-health), especially the role of women's education, which has been identified as a causal factor for healthcare utilization and maternal health outcomes in settings such as Peru and Uganda.[14](https://www.sciencedirect.com/science/article/pii/S2589537024002323" \l "bib14),[15](https://www.sciencedirect.com/science/article/pii/S2589537024002323" \l "bib15) In addition to examining the impact of women's education on maternal health outcomes, understanding the impact of geography (e.g., urban/rural location) on [reproductive health](https://www.sciencedirect.com/topics/medicine-and-dentistry/reproductive-public-health) factors and health system access can help inform policies to improve health equity within countries.

1. Citation: Trends in maternal mortality estimates 2000 to 2023: estimates by WHO, UNICEF, UNFPA, World Bank Group and UNDESA/Population Division. Geneva: World Health Organization; 2025. Licence: CC BY-NC-SA 3.0 IGO
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### Existing Use of Machine Learning Methods in Public Health