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Estimates of Under-Five Mortality From a Mobile Phone Survey During the COVID-19 Outbreak: An Observational Study Comparing Three Instruments in Malawi

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ABSTRACT Under-five mortality estimates for low- and middle-income countries are primarily derived from detailed birth or pregnancy histories collected through in-person household surveys. Such surveys are, however, resource intensive and vulnerable to interruption during epidemic outbreaks and other crises. Remotely deployed mobile phone surveys can circumvent these disadvantages, but their suitability for measuring population-level mortality has not been demonstrated. In this contribution, we examine Malawian mobile phone survey data from the Summary Birth Histories, Truncated Pregnancy Histories, and Full Pregnancy Histories instruments for estimating under-five mortality. Considering the limited penetration and the unequal distribution of mobile phones in Malawi, quota sampling was used to ensure representation of population subgroups where mobile phone ownership is low, and poststratification methods were applied to further attenuate selection bias. Resulting probabilities of dying, or $q(x)$—before 28 days, 12 months, and 60 months of life—are compared against external estimates from a recent Demographic and Health Survey, a Multiple Indicator Cluster Survey, and model-based estimates from the UN Inter-agency Group of Child Mortality Estimation. Mobile phone survey estimates using the Summary Birth Histories capture the historical trends of $q(12m)$ and $q(60m)$ up to 2018, but they are less reliable for the most recent years. Compared with external sources, estimates from the Truncated Pregnancy Histories appear to be biased downward. Estimates of $q(28d)$, $q(12m)$, and $q(60m)$ from the Full Pregnancy Histories are in line with those published by the UN Inter-agency Group, but they are also suggestive of a mortality excess during the COVID-19 outbreak in 2020–2022. We conclude that mobile phone surveys are a promising method for collecting under-five mortality data, and particularly so via the Full Pregnancy Histories instrument.

KEYWORDS Child mortality estimation • Mobile phone surveys • Full and truncated pregnancy histories • Bayesian Poisson regression • Malawi

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Introduction and Background

Under-five mortality estimates for low- and middle-income countries are usually derived from survey data, including the Demographic and Health Surveys (DHS) and the Multiple Indicator Cluster Surveys (MICS) (Sharrow et al. 2022). Most of these surveys rely on face-to-face data collection and were interrupted during the early stages of the COVID-19 outbreak, limiting the scope of mortality surveillance during the epidemic. Mobile Phone Surveys (MPS) constitute an appealing alternative that can be implemented promptly, more cheaply, and without face-to-face contact. The latter aspect also makes them reasonable for field implementation during epidemic outbreaks and mortality crises (Kuehne et al. 2016). However, our experience with mortality MPSs remains limited. Their suitability for measuring population-level mortality—and under-five mortality in particular—is not well-established, and the possible biases in the ensuing estimates are not well-understood.

As our experience with MPS mounts, we are gradually gaining insight into some of the methodological caveats—for example, acceptability, sample selection, reporting errors—and possible remedies. One noninferiority trial from Malawi suggested that respondents agree to take part in a mortality MPS in the same proportions as in an MPS focused on socioeconomic topics (Chasukwa et al. 2022). Another survey, again from Malawi, indicated that MPS data quality is less dependent on interview duration than is often assumed (Torrisi et al. 2024). Data quality, however, remains a concern with MPS. For example, there is evidence of higher levels of age heaping in MPS than in face-to-face surveys (Helleringer et al. 2023). Sample selection is another important systemic problem because mobile ownership and usage are unequally distributed, response rates are typically low, and sampling frames are not always readily available (Greenleaf et al. 2020; LeFevre et al. 2020). In practical applications, sample selection bias can be alleviated by pre- and poststratification procedures, but these may not apply to all demographic and health indicators of interest (Ahmed et al. 2024; Greenleaf et al. 2020; Sánchez-Páez et al. 2023).

In this contribution, we use data from the Malawi Rapid Mortality Mobile Phone Survey (RaMMPS) for estimating under-five mortality (U5M) and compare the estimates using three survey instruments—Summary Birth Histories (SBH), Full Pregnancy Histories (FPH), and Truncated Pregnancy Histories (TPH)—to ascertain which instrument is best suited for a MPS. Considering the limited penetration and the unequal use of mobile phones in Malawi, we implemented a quota sampling strategy, and we use poststratification weighting to reduce the selection bias. The FPH questions were modeled after the instrument that was first used in DHS round VIII (Akuze et al. 2021). TPH left-censor the pregnancies with an end date more than seven years before the interview. Unlike FPH, the TPH were recorded in reverse chronological order, an approach that was adapted from the Malaria Indicator Surveys, albeit in that case focusing on births rather than pregnancies (Masquelier et al. 2023). In comparison to FPH, the appeal of the two other instruments is that they are shorter and therefore perhaps more suitable for rapid assessments and for interviews over the phone. However, the trade-off between survey duration and validity of pregnancy histories has not been formally assessed. Estimates from all three instruments used in RaMMPS are compared with each other and with estimates from DHS, the MICS, and the UN Inter-agency Group for Child Mortality Estimation (UN IGME) (2025).

Data

Sampling and Study Design

The fieldwork for the Malawi Rapid Mortality Mobile Phone Survey was coordinated by the Institute of Public Opinion and Research between January 24, 2022, and July 28, 2023. Using the mobile phone numbering structure in Malawi, a set of random numbers was generated by Sample Solutions and verified against a database of registered and prepaid numbers on the GSM network (the Home Location Register). From this pool of numbers, random digit dialing with active strata monitoring was used to constitute the sample (Labrique et al. 2017). Strata were a priori defined in terms of broad age groups (18–49 and 50–64), sex, region (North, Central, and South), and type of place of residence (urban or rural) and based on the population distribution in the 2018 national census (National Statistical Office 2019). Once a stratum was filled, respondents with these attributes were no longer eligible to participate in the study. Fieldwork was structured in four blocks of data collection—ranging from 3.6 to 6.2 months—with quotas for each stratum reset at the conclusion of each block. As described elsewhere, interactive voice response surveys were used to fill the quotas for harder to reach population subgroups, rural women in particular (Tlhajoane et al. 2025). Minors younger than 18 were not interviewed to ensure that all respondents were in a position to consent to the interviews themselves. Sampling was done without replacement.

Survey Instruments

SBH is a short-form questionnaire used to enumerate the children ever born and the children alive by the time of the interview. As done in the DHS, these questions were asked for each sex separately and included a probe for children not currently living in the household of the mother. Along with respondents' attributes (e.g., age), these questions are used to estimate infant and under-five mortality rates indirectly using the Brass technique (Hill 2013b). During the first fieldwork block, a SBH questionnaire was administered to all adult women of reproductive age who consented to participate.

Starting on May 26, 2022—with the second block of data collection—consenting women aged 18–49 were randomly allocated to either the TPH or FPH questions. The SBH module continued to be administered to respondents in the FPH group. A summary of the data collection schedule is described in Table 1. Instruments were adapted from existing questionnaires and solicit information on pregnancy outcomes, delivery dates, time of gestation, and the survival status of children. This information allows estimating the exposure to the risk of dying and dating of deaths. The TPH and FPH further included probes for any evidence of life (e.g., breathing, moving, or crying) at the time of delivery to separate live births from stillbirths.

TPH were collected in reverse chronological order, starting with the most recent pregnancy—if any—and ended whenever the last reported outcome predates the survey by more than seven years. Conversely, individuals who were allocated to the FPH reported pregnancies in chronological order starting with the first pregnancy.

Table 1 Number of interviews by instrument and round of data collection

	SBH		TPH		FPH/SBH		Total	
Round of Data Collection	Interviews	Excluded	Interviews	Excluded	Interviews	Excluded	Interviews	Excluded
1. From January 24, 2022, to May 25, 2022	1,763	7	0	0	0	0	1,763	7
2. From May 26, 2022, to September 13, 2022	0	0	651	5	668	6	1,319	11
3. From September 14, 2022, to March 20, 2023	0	0	881	2	817	2	1,698	4
4. From March 21, 2023, to July 28, 2023	0	0	569	1	595	5	1,164	6
Total	1,763	7	2,101	8	2,080	13	5,944	28

Notes: For consistency, FPHs also collect SBHs (i.e., total number of children alive and total number of children ever born). Because of missing values, excluded interviews cannot be used to estimate poststratification weights. SBH = Summary Birth Histories. TPH = Truncated Pregnancy Histories. FPH = Full Pregnancy Histories.

Births and stillbirths were recorded in exact—or approximated—dates (e.g., month-day-year or month-year), and ages at death were recorded within days for the first month of life, in months for the remainder of the first year and the second year of life, and in years after the second birthday. The TPH questionnaire is an adaptation of the Malaria Indicator Surveys; the FPH instrument was modeled after Phase 8 of the DHS Standard Questionnaire.

The time to administer the different questionnaire modules was recorded starting on March 22, 2023. The average durations were 2.17 minutes and 3.88 minutes for the TPH and FPH questionnaire modules, respectively. Although the FPH instrument takes, on average, almost twice the time to administer as the TPH, the dispersion around these durations is large because some interviews can take more than three times the average value (Figure A1, shown in the online appendix, along with all other figures and tables designated with an "A").

Methods

Poststratification Weights

The share of mobile phone subscribers per 100 individuals in Malawi is estimated at 61%, which falls well short of the average in sub-Saharan Africa (excluding high income), where mobile phone penetration was estimated at 93% in 2023 (World Bank 2026). Ownership among women is lower (45.60% in 2017 and 59.72% in 2021) than among men (55.72% and 63.45%, respectively), as calculated from the Global Financial Inclusion (Findex) Databases of 2017 and 2021 (Demirgüç-Kunt et al. 2022; Demirgüç-Kunt et al. 2018). Among women aged 18–49, mobile phone

ownership is estimated at 36.19% in the DHS VII (2015–2016) and 37.84% in the MICS 6 (2019–2020). Because mobile phone ownership correlates with sociodemographic background characteristics, which are, in turn, associated with mortality, this correlation is likely to introduce bias in the estimates. The imposition of quotas only partially alleviates this problem, because quotas are limited to a number of key demographic (i.e., age and sex) and geographic attributes (i.e., region and urban/rural place of residence). Imposing quotas on a more extensive set of characteristics would be challenging because it would considerably slow down fieldwork, as it becomes increasingly difficult to identify individuals with the desired combination of attributes. We therefore resorted to poststratification to ensure that the RaMMPS sample is representative of the entire population in terms of a broader set of sociodemographic background characteristics. Poststratification also resolves remaining imbalances in the dataset whenever some of the quotas could not be filled.

Using the subsample of 5,916 adult women of reproductive age, poststratification weights were estimated by iterative proportional fitting or raking (Deville et al. 1993; Stephan 1942), a method that is routinely used in MPS (Dal Grande et al. 2015). This approach ensured that the marginal distributions of the weighting variables were matched to the population of adult women of reproductive age (18–49) in the Malawi DHS VII. Poststratification weights were truncated below and above the 2.5th and 97.5th percentiles to avoid the extreme values. For each data collection block, poststratification weights were estimated for the following set of background characteristics: (1) urban versus rural place of residency; (2) region (North, Central, or South); (3) age group of the respondent (18–29, 30–39, or 40–49); (4) educational attainment (less than complete primary, complete primary and incomplete secondary, or complete secondary or more); (5) household size (1–4, 5–8, or 9+); and (6) the availability of electricity in the household (yes/no). Other household amenities, such as the source of drinking water (safe/unsafe) and roof material (durable or not), were used for testing the accuracy of the poststratification adjustment by comparing the RaMMPS adjusted values with those estimated from the DHS VII. The distribution of poststratification weights—comparing RaMMPS with other sources—is given in Figure A2.

Uncertainty

Descriptive statistics and direct and indirect mortality estimates of under-five mortality are reported along with bootstrapped confidence intervals (CIs) (Efron and Tibshirani 1993). To that end, birth histories were resampled 5,000 times with replacement. For each bootstrap sample, the probability of selection was proportional to the poststratification weight of the mother—that is, the higher the weight, the greater the chance of being resampled. As one of the advantages of bootstrapping, empirical distributions of all indicators of under-five mortality, $q(x)$, were estimated without relying on parametric assumptions. The 50th percentile of these distributions is reported as the measure of central tendency, and the 2.5th and 97.5th percentile points were used to report 95% uncertainty bounds.

Bootstrapped CIs were also estimated for the DHS VII and the MICS 6. These two are multistage surveys, which first select the clusters and then the households within each cluster. Our CIs depart from the classic approach of resampling the clusters

within the same strata of the survey, as we resample women aged 15–49 within each cluster or primary sampling unit. From this perspective, the geographic distribution of clusters and the number of women of reproductive age are held constant, thus the resulting CIs express the randomness of interviewing more or fewer adult women, women with varying numbers of children, and respondents whose children experience higher or lower levels of mortality.

Indirect Estimates Using Summary Birth Histories

Brass-type estimates of infant— $q(12m)$—and under-five mortality— $q(60m)$—were derived from average proportions of deceased children tabulated by five-year age groups of mothers. This represents the Trussell variant of the method, as detailed in *Manual X: Indirect Techniques for Demographic Estimation* (United Nations 1983: chap. 3). This approach allows estimation of the probability of dying— $q(x)$—before 1, 2, 3, 5, 10, 15, and 20 years, as well as their corresponding reference periods. Model life tables were used to recover the estimated values at 12 and 60 months, and the resulting probabilities of dying were interpolated to produce mortality estimates at regular time intervals from January 1, 2006, to January 1, 2018. Considering the relatively higher burden of child mortality—from ages one to five—to the under-five mortality, the Coale–Demeny North family was assumed to best represent the age patterns of under-five mortality in Malawi (Coale and Demeny 1966). The sensitivity of this premise is assessed in Figure A3. We discarded estimates closer to the date of the survey (i.e., those relying on data from the youngest women only) owing to the well-known underperformance of the method (Ewbank 1982; Silva 2012). CIs of Brass-type estimates of $q(12m)$ and $q(60m)$ were calculated by iterating the same procedure for each bootstrapped sample.

Direct Estimates Using Pregnancy Histories

Mortality schedules $q(x)$—from zero to five years—were calculated from TPH and FPH while applying Hill's direct method (Hill 2013a) and assuming constant mortality rates in each age interval to recover the probabilities of dying from age-specific death rates, ${}_nm_x$. Considering the fast decline in the force of mortality during the first weeks and months of life, the latter is a reasonable assumption for narrow age intervals as used in Guillot et al. (2022). Mortality rates were calculated as the number of deaths over the exposure time in each detailed-age interval (i.e., weeks during the first month of life, months to complete the first year, trimesters during the second year, and then years of life until age five). From these rates, we derived the neonatal mortality rate, $q(28d)$, the infant mortality rate, $q(12m)$, and the under-five mortality rate, $q(60m)$—formally defined as probabilities of dying. All mortality indicators were estimated for 9+ years of retrospection, from January 1, 2014, to the date of the interview, and also by subperiods of two years each—except for the one starting on January 1, 2022. Truncation limits the scope of the retrospection. Because TPH do not include children born before January 1, 2014, events and exposure time are poorly represented for the earlier periods of analysis.

Both TPH and FPH collect information in terms of the age and—if applicable—age at death in completed days, months, or years rather than in exact age, and some uncertainty is associated with these approximations. Bootstrapped samples assume an exact date of birth (i.e., day-month-year) and an exact age at death using a uniform distribution. The main advantage of accounting for this uncertainty is to avoid the coarse assumption that all births and deaths occur on the midpoint of the interval.

Assessing the Sex and Time Variation of Under-Five Mortality

To evaluate sex differences in U5M as well as changes over time, we used a proportional hazards regression—assuming a Poisson likelihood and quantifying individual-level deviations from the population mortality rates. As described by Eq. (1) for any reported child j surviving to the age x, the expected event of dying in an age interval $[x, x+n)$—denoted by $\lambda_j(x)$—is a function of the population-level mortality rate $m(x)$; a set of individual characteristics, where z_j^k represents one of them; age–period markers, each denoted by $y_j^p(x)$; and the exposure time within the same age interval $t_j(x)$:

$$\ln\left(\lambda_j\left(x\right)\right) = \ln\left(m\left(x\right)\right) + \sum_k z_j^k \cdot \beta_k + \sum_p y_j^p\left(x\right) \cdot \gamma_p + \ln\left(t_j\left(x\right)\right). \quad (1)$$

The associated coefficients β and γ quantify any additional risk of mortality relative to the population-level value and related to the baseline characteristics or the period of exposure. The set of individual characteristics is assumed to be time invariant and includes the sex of the child (male = 1, female = −1, and 0 if unknown), the place of residence (urban = 1 and rural = −1), the country region (North, Central, or South), the age group of the mother (less than 30 = 1 and 30 or more = −1), and the level of education of the mother (incomplete primary, complete secondary, or complete secondary or more)—as reported at the time of the interview. The age–period markers indicate if a child j—of age x to $x+n$—was exposed to the risk of dying in a particular period of time, and we assumed five intervals starting on January 1, 2014, breaking every two years and ending with the date of the interview. The exposure time $t_j(x)$ is an offset variable—directly calculated—and quantifies the number of years that a child j lived between the exact ages of x and $x+n$.

Because the age–period markers are mutually exclusive categorical variables, our identifying restriction is to estimate the coefficients β and γ, to be conditional on a predefined value of $m(x)$. This offset variable is age-specific, is constant within the age interval, and was calculated directly from population-level quantities—that is, by dividing the total number of deaths by the estimated exposure time of all children in the same age interval—describing the case of all regression coefficients equal to 0. Hence, the coefficients β and γ—resulting from the regression analysis—will capture excess mortality as an overall departure from the observed age pattern of U5M defined from January 1, 2014, to the last day of data collection and for both sexes combined.

Bayesian Poisson regression has long been fundamental to analyzing aggregated-level mortality outcomes—for example, death counts by country–years, subnational data, or small-area estimates (Alexander and Alkema 2018; Alexander et al. 2017; Dharamshi et al. 2025; Loquiha et al. 2018). Because mortality is a one-time

absorbing event, analyzing individual-level mortality data implies the use of a Poisson likelihood defined for a binary outcome—that is, dead or alive (Crowther et al. 2012; Fagbamigbe et al. 2021; Loomis et al. 2005; Schumacher et al. 2022).

Given the parameters of the model, β, γ, and $m(x)$, Eq. (2) describes the Poisson likelihood of observing $d(x)$ deaths among children who were exposed to the risk of dying from x to $x+n$ years. Here $d_j(x)$ takes the value of 1 if the child j dies from age x to $x+n$ and 0 otherwise; w_j corresponds to her relative weight, which has been adjusted from the mother's poststratification weight such that $\sum_{j=1}^{N} w_j = N$, where N denotes the number of children who survived to the age x:

$$p\left(d\left(x\right) \mid m\left(x\right);\beta,\gamma\right) = \prod_{j=1}^{N}\left[\lambda_j\left(x\right)^{d_j\left(x\right)} \cdot e^{-\lambda_j\left(x\right)}\right]^{w_j}. \tag{2}$$

A likelihood function can be constructed for each age interval, defined by these exact age cutoff points: 0, 7, 14, 21, and 28 days; 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 15, 18, and 21 months; and 2, 3, 4, and 5 years—each of them depending on the parameters β and γ and a mortality rate $m(x)$ specific to that age interval. We fit the model to the observed data, maximizing the combined likelihood P, resulting from the product of all age-specific likelihoods, as shown in Eq. (3). Hence, the estimated values of β and γ capture the overall influence of individual characteristics on mortality rates for all ages:

$$\mathrm{P}\left(d\left(0\right),\ldots,d\left(4y\right) \mid m\left(0\right),\ldots,m\left(4y\right);\beta,\gamma\right) = \prod_{x} p\left(d\left(x\right) \mid m\left(x\right);\beta,\gamma\right). \tag{3}$$

The parameters β and γ were estimated from the Bayesian perspective of the Hamiltonian Markov chain Monte Carlo method (Neal 2011), using the No-U-Turn Adaptive Sampler to efficiently determine the length and direction of each trajectory or Hamiltonian dynamic (Hoffman and Gelman 2014). Each parameter was assigned a weakly informative prior from a Gaussian distribution centered at 0 and assuming a standard deviation equal to 1—that is, $\beta_k \sim \mathcal{N}(0,1^2)$ and $\gamma_t \sim \mathcal{N}(0,1^2)$. A total of 5,000 samples of these parameters were generated after a warm-up period of 250 iterations. Between 22% and 38% of the samples were rejected. The posterior distribution of the parameters was used to report the central tendency and uncertainty bounds, corresponding to the percentiles 50th, 2.5th, and 97.5th. Replication materials are available in the GitHub repository at https://github.com/Romero-Prieto/RaMMPS_U5M.

The Bayesian perspective brings some advantages to the analysis of U5M. Given an exposure time, we can predict the expected number of deaths for different ages and periods depending solely on the estimated coefficients of each generated set of parameters. Hence, these predictions can be used to reconstitute the samples of $q(x)$ associated with the posterior distribution of the estimated coefficients and the uncertainty of the model.

Given how the sex of the child is coded, the resulting coefficient increases the hazard for one sex while decreasing it by the same magnitude for the other. Hence, the sex ratio—male to female—of the probability of dying before exact age x can be estimated from Eq. (4), at a given value of $q(x)$, the coefficient β_{sex}, and keeping constant the same exposure to the risk of dying:

$$Sex\ Ratio\ of\ q(x) = \frac{1-\left[1-q(x)\right]^{e^{\beta_{sex}}}}{1-\left[1-q(x)\right]^{e^{-\beta_{sex}}}}. \quad (4)$$

Results

Descriptive Statistics

Table 2 provides sociodemographic background characteristics of respondents by survey instrument in the Malawi RaMMPS. A total of 3,823 women aged 18–49 had nonmissing data to estimate poststratification weights and completed the SBH questionnaire. The samples for the TPH and FPH modules were 2,093 and 2,067, respectively. Table 2 also shows the distribution of background characteristics of women of reproductive age in the MICS 6 and the DHS VII, including the subset of women who owned a mobile phone. After the application of the poststratification weights, the univariate distributions of the RaMMPS background characteristics of the three groups of respondents are comparable to the DHS. It is worth noting that weighting introduced important corrections for type of place of residence, household size, level of education, and access to electricity because these attributes tend to correlate with mobile phone ownership (Sánchez-Páez et al. 2023). Although the source of drinking water and the roof material were household characteristics not used for poststratification, the weighting strategy introduces corrections in the expected direction.

As a data validity check, we report in Table 3 a number of demographic indicators that are also derived from birth history modules but are not directly related to mortality. We provide weighted (i.e., poststratified) and unweighted (i.e., selected and potentially biased) estimates and compare these with those from the DHS and MICS. It is worth noting that the RaMMPS data are restricted to women aged 18 or older, and we also imposed these age bounds for these external data sources. However, we provide an estimate derived from all women aged 15–49 to examine the potential bias of using a sample that is selecting only adult women. The first two rows of the DHS and MICS estimates are for the entire sample, use the survey sampling weights, and include/exclude women aged 15–17. The last row of these estimates pertains to the subsample of mobile phone owners and compares adjusted estimates—based on poststratified weights—with naive and potentially biased estimates, which rely solely on the sampling weights and do not account for the problem of selection.

The percentage of childless women computed from the RaMMPS data was considerably higher than expected. To a lesser extent, this was also the case for the DHS subset of mobile phone owners at 15.32% (95% CI: 14.27–16.39%) compared with the full sample of all adult women of reproductive age at 12.46% (95% CI: 11.90–13.02%), as well as for the MICS subset of mobile phone owners at 14.74% (95% CI: 13.71–15.83%) compared with the full sample at 12.33% (95% CI: 11.70–12.95%). Poststratification overcorrects this metric of fertility because poststratified estimates are lower than expected: 11.82% (95% CI: 10.86–12.77%) in the case of the DHS and 10.79% (95% CI: 9.79–11.83%) in the case of the MICS, but confidence bounds

Table 2 Descriptive statistics by survey instrument (before and after poststratification)

	SBH		TPH		FPH		MICS 6, Women 18–49		DHS VII, Women 18–49	
Attribute	Poststrat.	Selected	Poststrat.	Selected	Poststrat.	Selected	All	Mobile Owners	All	Mobile Owners
Place of Residence:										
Urban	18.13 [16.92, 19.36]	31.44 [29.98, 32.96]	18.82 [17.20, 20.50]	37.17 [35.12, 39.20]	17.85 [16.21, 19.55]	37.78 [35.70, 39.91]	18.25 [17.97, 18.52]	33.99 [32.99, 34.98]	18.42 [18.16, 18.66]	35.41 [34.43, 36.36]
Region										
North	11.25 [10.25, 12.24]	16.45 [15.30, 17.66]	12.37 [10.99, 13.76]	17.06 [15.43, 18.73]	10.89 [9.58, 12.24]	16.50 [14.90, 18.14]	10.95 [10.79, 11.12]	14.51 [13.90, 15.12]	11.69 [11.53, 11.84]	15.04 [14.44, 15.67]
Central	43.53 [41.96, 45.04]	37.67 [36.07, 39.16]	40.99 [38.84, 43.14]	36.55 [34.50, 38.60]	44.36 [42.19, 46.49]	37.35 [35.17, 39.36]	45.86 [45.52, 46.19]	40.47 [39.33, 41.59]	42.85 [42.53, 43.15]	40.69 [39.56, 41.73]
South	45.23 [43.66, 46.74]	45.88 [44.28, 47.48]	46.63 [44.43, 48.73]	46.39 [44.31, 48.59]	44.75 [42.53, 46.88]	46.15 [43.98, 48.38]	43.19 [42.87, 43.50]	45.01 [43.94, 46.08]	45.47 [45.17, 45.77]	44.28 [43.23, 45.33]
Age										
18–29	53.31 [51.69, 54.88]	57.23 [55.69, 58.83]	50.22 [48.11, 52.32]	56.90 [54.80, 59.10]	54.14 [51.96, 56.31]	58.10 [55.93, 60.14]	51.70 [50.79, 52.66]	47.09 [45.61, 48.57]	52.42 [51.60, 53.25]	50.05 [48.64, 51.49]
30–39	29.82 [28.35, 31.25]	29.40 [28.01, 30.79]	33.06 [31.10, 35.07]	30.58 [28.57, 32.54]	28.79 [26.87, 30.75]	28.74 [26.85, 30.72]	30.24 [29.37, 31.10]	34.35 [32.93, 35.83]	30.80 [30.04, 31.57]	34.11 [32.73, 35.48]
40–49	16.87 [15.69, 18.07]	13.34 [12.27, 14.41]	16.67 [15.15, 18.35]	12.52 [11.13, 13.95]	17.08 [15.43, 18.70]	13.21 [11.76, 14.66]	18.04 [17.37, 18.73]	18.56 [17.44, 19.69]	16.79 [16.17, 17.41]	15.83 [14.83, 16.85]
Education										
Less than complete primary	65.11 [63.59, 66.54]	14.23 [13.13, 15.35]	64.60 [62.57, 66.60]	14.72 [13.26, 16.27]	65.31 [63.28, 67.30]	14.27 [12.77, 15.82]	59.66 [58.85, 60.46]	38.59 [37.17, 39.97]	64.65 [63.96, 65.36]	42.07 [40.74, 43.40]
Incomplete secondary	24.69 [23.33, 26.08]	31.34 [29.90, 32.85]	24.63 [22.84, 26.47]	29.89 [27.95, 31.77]	24.67 [22.84, 26.51]	30.72 [28.79, 32.75]	27.34 [26.57, 28.15]	33.70 [32.34, 35.08]	24.74 [24.04, 25.42]	33.34 [32.00, 34.65]
Complete secondary or more	10.23 [9.29, 11.14]	54.41 [52.84, 56.00]	10.75 [9.51, 12.14]	55.38 [53.27, 57.53]	10.01 [8.76, 11.32]	55.01 [52.78, 57.14]	12.99 [12.39, 13.58]	27.71 [26.40, 29.05]	10.61 [10.12, 11.10]	24.60 [23.40, 25.83]

Table 2 (continued)

	SBH		TPH		FPH		MICS 6, Women 18–49		DHS VII, Women 18–49	
Attribute	Poststrat.	Selected	Poststrat.	Selected	Poststrat.	Selected	All	Mobile Owners	All	Mobile Owners
Household Size										
1–4	41.56	37.88	37.79	35.26	42.57	38.80	46.34	46.53	40.45	41.28
	[39.99, 43.16]	[36.32, 39.42]	[35.74, 39.89]	[33.25, 37.31]	[40.49, 44.75]	[36.67, 40.93]	[45.44, 47.29]	[45.06, 48.05]	[39.64, 41.24]	[39.87, 42.69]
5–8	51.77	52.60	55.09	54.66	50.90	52.10	48.70	48.34	52.74	52.04
	[50.20, 53.39]	[51.01, 54.17]	[52.84, 57.10]	[52.51, 56.76]	[48.77, 53.02]	[49.98, 54.28]	[47.78, 49.61]	[46.86, 49.84]	[51.94, 53.58]	[50.63, 53.49]
9+	6.64	9.52	7.12	10.08	6.48	9.10	4.95	5.12	6.80	6.69
	[5.89, 7.43]	[8.61, 10.46]	[6.07, 8.27]	[8.84, 11.42]	[5.47, 7.60]	[7.84, 10.35]	[4.61, 5.29]	[4.56, 5.72]	[6.42, 7.19]	[6.01, 7.39]
Electricity: Access	13.37	52.71	14.05	52.27	13.11	53.60	21.50	38.78	13.75	30.25
	[12.29, 14.41]	[51.09, 54.30]	[12.57, 15.58]	[50.07, 54.42]	[11.71, 14.61]	[51.45, 55.73]	[20.89, 22.13]	[37.47, 40.10]	[13.28, 14.20]	[29.09, 31.39]
Drinking Water: Safe Source	86.76	93.36	88.15	93.65	87.28	93.28	88.35	92.26	88.22	92.99
	[85.68, 87.84]	[92.55, 94.17]	[86.77, 89.54]	[92.64, 94.70]	[85.82, 88.73]	[92.16, 94.34]	[87.84, 88.86]	[91.50, 93.01]	[87.78, 88.63]	[92.34, 93.62]
Roofing: Durable Material	56.68	80.91	59.39	81.65	57.43	81.42	55.95	77.59	48.47	71.92
	[55.15, 58.23]	[79.62, 82.11]	[57.19, 61.44]	[79.98, 83.23]	[55.30, 59.51]	[79.75, 83.07]	[55.19, 56.72]	[76.52, 78.71]	[47.79, 49.13]	[70.73, 73.07]
Number of Observations	3,823	3,823	2,093	2,093	2,067	2,067	21,124	8,363	21,392	8,151

Notes: Values are the median of a bootstrapped distribution, and the 2.5th and 97.5th percentiles are shown in square brackets. DHS VII and MICS 6 estimates are provided as a reference. Columns for TPH, FPH, and DHS VII reproduce estimates from Reniers et al. (2025), which analyze stillbirth and perinatal mortality for the same groups of women, but in this table they are based on 5,000 bootstrap resamples with replacement. SBH = Summary Birth Histories. TPH = Truncated Pregnancy Histories. FPH = Full Pregnancy Histories. Poststrat. = poststratified.

Table 3 The percentage of childless women, the average parity, the total fertility rate (TFR) among women aged 18–49, and the sex ratio at birth (SRB) by type of RaMMPS instrument and weighting

	% of Childless Women		Average Parity		TFR		SRB	
Instrument	Poststrat.	Selected	Poststrat.	Selected	Poststrat.	Selected	Poststrat.	Selected
TPH					2.32	2.06	0.90	0.93
					[2.08, 2.58]	[1.84, 2.29]	[0.83, 0.98]	[0.86, 1.02]
FPH	12.72	28.06	2.51	1.79	2.44	2.11	0.90	0.95
	[11.27, 14.18]	[26.22, 30.04]	[2.43, 2.59]	[1.71, 1.86]	[2.22, 2.67]	[1.88, 2.35]	[0.85, 0.95]	[0.89, 1.01]
SBH	12.61	28.22	2.67	1.90			0.92	0.96
	[11.56, 13.68]	[26.80, 29.61]	[2.61, 2.73]	[1.84, 1.95]			[0.89, 0.96]	[0.91, 1.00]
DHS VII								
Women aged 15–49	22.52		2.79		4.40		1.00	
	[21.88, 23.19]		[2.75, 2.82]		[4.31, 4.50]		[0.99, 1.02]	
Women aged 18–49	12.46		3.18		4.14		1.00	
	[11.90, 13.02]		[3.15, 3.22]		[4.05, 4.24]		[0.98, 1.02]	
Women aged 18–49, mobile owners	11.82	15.32	3.11	2.79	3.27	2.96	0.98	1.00
	[10.86, 12.77]	[14.27, 16.39]	[3.04, 3.18]	[2.73, 2.85]	[3.12, 3.42]	[2.84, 3.10]	[0.95, 1.02]	[0.97, 1.04]
MICS 6								
Women aged 15–49	23.02		2.62		4.17		1.01	
	[22.30, 23.76]		[2.58, 2.66]		[4.07, 4.26]		[0.99, 1.03]	
Women aged 18–49	12.33		3.01		3.92		1.01	
	[11.70, 12.95]		[2.97, 3.05]		[3.82, 4.02]		[0.99, 1.03]	
Women aged 18–49, mobile owners	10.79	14.74	3.08	2.78	3.38	2.99	0.95	0.99
	[9.79, 11.83]	[13.71, 15.83]	[3.00, 3.16]	[2.71, 2.84]	[3.19, 3.56]	[2.85, 3.12]	[0.91, 0.99]	[0.95, 1.02]

Notes: Values are the median of a bootstrapped distribution, and the 2.5th and 97.5th percentiles are shown in square brackets. The percentage of childless women is calculated at the time of the survey. The TFR is a three-year period estimate, ending on the median date of data collection in MICS 6 and DHS VII. The RaMMPS fertility measure extends to the last day of data collection. The SRB is calculated for all reported births. TFR = total fertility rate. SRB = sex ratio at birth. RaMMPS = Malawi Rapid Mortality Mobile Phone Survey. SBH = Summary Birth Histories. TPH = Truncated Pregnancy Histories. FPH = Full Pregnancy Histories. Poststrat. = poststratified.

overlap. Comparing women aged 18–49 with all women of reproductive age, both DHS and MICS are suggestive of downward bias related to age selection. Note that age selection bias and the mobile ownership selection bias have opposite signs. While the age selection drastically reduces the percentage of childless women, the selection of mobile phone owners produces a modest but still significant increase in this percentage. In the case of RaMMPS data, poststratification weighting results in a downward adjustment from 28.06% (95% CI: 26.22–30.04%) to 12.72% (95% CI: 11.27–14.18%) in the case of the FPH instrument and from 28.22% (95% CI: 26.80–29.61%) to 12.61 (95% CI: 11.56–13.68%) in the case of the SBH.

The average parity is also affected by selection in terms of age and mobile phone ownership. Estimates for the DHS and MICS suggest that the exclusion of minors increases the average parity, and the selection in terms of mobile phone ownership is in the opposite direction. Mobile phone owners in the DHS have fewer children than the general population estimate—2.79 (95% CI: 2.73–2.85) versus 3.18 (95% CI: 3.15–3.22)—but poststratification weighting largely corrects this bias. Although the poststratification of the RaMMPS data produces a correction in the same direction, the resulting estimates remain lower than in the DHS or MICS. After poststratification, the mobile phone survey estimates are 2.51 (95% CI: 2.43–2.59) and 2.67 (95% CI: 2.61–2.73) for the FPH and SBH instruments, respectively. Because the TPH instrument is by design not exhaustive, the average parity cannot be calculated for these women.

The RaMMPS pregnancy history modules also produce lower than expected estimates of the total fertility rate (TFR; here a three-year period estimate, restricted to women aged 18–49). Poststratification weighting produces an upward adjustment, but not to the extent that the RaMMPS estimates approach those from the DHS and the MICS. In the case of the TPH module, for example, the TFR increased from 2.06 (95% CI: 1.84–2.29) to 2.32 (95% CI: 2.08–2.58) after poststratification, whereas the full population sample estimate of the TFR from the DHS is 4.40 (95% CI: 4.31–4.50) and from the MICS is 4.17 (95% CI: 4.07–4.26)—bearing in mind that these values are significantly underestimated owing to the selection of women aged 18–49, which is censoring the left-hand tail of the fertility schedule. Poststratification weighting does not introduce a significant correction in either TPH or FPH estimates. It is also worth noting that poststratification applied to the mobile phone owners does not recover to the full sample estimate, from either DHS or MICS. This limitation has previously been documented by Sánchez-Páez et al. (2023) for 34 low- and middle-income countries using the DHS.

For the year 2017 and using multiple retrospective sources such as the DHS, Malaria Indicator Surveys, and MICS, the sex ratio at birth (SRB) in Malawi is estimated to be 1.01 male live births per female birth, and this corroborates estimates for other sub-Saharan African populations (Chao et al. 2019). With the exception of the TPH instrument, the values computed from the RaMMPS data were marginally lower and well within the bounds of statistical uncertainty. DHS and MICS estimates in Table 3 show that the SRB is not influenced by the exclusion of minors nor by the selection on mobile phone ownership. As expected, poststratification weighting did not make a substantial difference in this case.

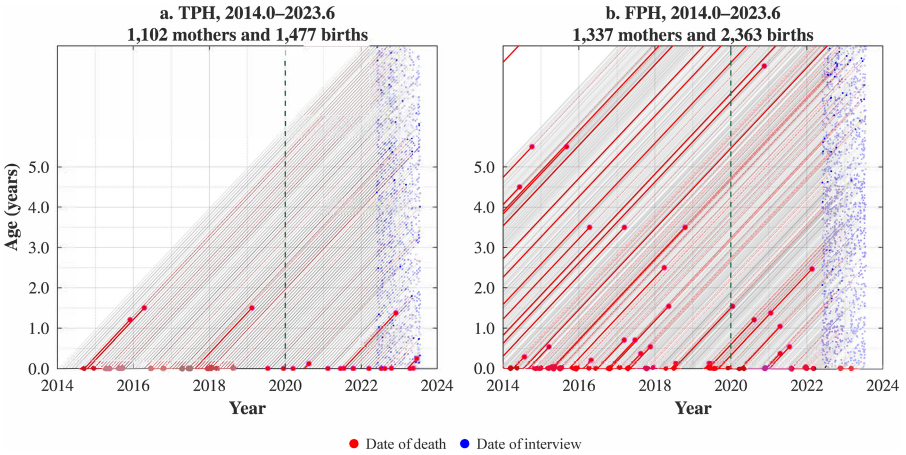

Fig. 1 Lexis diagrams by type of pregnancy history implemented by RaMMPS: (a) Truncated Pregnancy Histories versus (b) Full Pregnancy Histories. Each child is represented by a diagonal, partially transparent line running upward from the date of birth to the date of the survey, the latter indicated by a blue dot. Overlapping dates of birth make the lifelines look darker. The lifelines for children who did not survive are plotted in red, marked with a red dot at the presumable date of death, and extended to the interview dates using a dashed, partially transparent red line.

Mortality Estimates

Figure 1 presents Lexis diagrams representing the lifelines and deaths from January 1, 2014, to the date of the interview for all children reported in the TPH and FPH modules. A similar representation of the data is not possible for the SBHs because the instrument does not capture detailed dates of the events. Children who were alive at the day of the interview are represented by a gray line and those who died by a red line—dotted after the date of death. The TPH instrument—in panel a—implies the shape of a triangle. A total of 1,102 women had a live birth after January 1, 2014, and they jointly reported on the survival status of 1,477 children. The FPH instrument—in panel b—extends the retrospective period to include all children younger than five on January 1, 2014. In total, 1,337 women reported on the survival status of 2,363 children in the FPH module. Both TPH and FPH were used to estimate neonatal, $q(28d)$, infant, $q(12m)$, and under-five mortality rates, $q(60m)$, from January 1, 2014, to July 28, 2023. Figure 1 illustrates the sparsity of the TPH data for capturing mortality data compared with the FPH, particularly beyond infancy, where age-specific mortality rates are low and the effective sample size is small.

Figure 2 presents two representations of the U5M indicators. The top row (panels a–c) shows 95% CIs of the neonatal (NMR), the infant (IMR), and the under-five (U5MR) mortality rates, comparing the RaMMPS data with the UN IGME estimates for all women aged 15–49, and the DHS VII and MICS 6 estimates restricted to women aged 18–49. These mortality rates are plotted on a time scale to highlight the differences in the reference period to which the estimates pertain. DHS and MICS data yield five-year estimates, ending on the average date of each survey, as data collection spanned

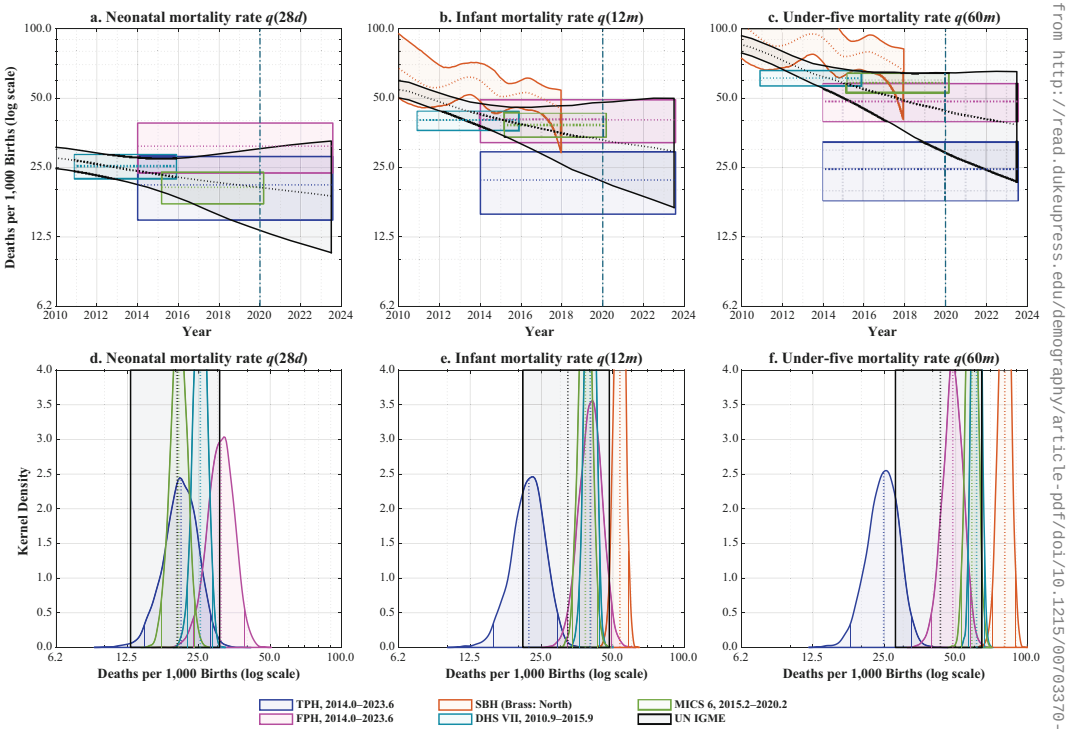

Fig. 2 Levels and distributions of the neonatal, infant, and under-five mortality rates by RaMMPS instrument (poststratified estimates), along with estimates from UN IGME (2025), the DHS, and the MICS. In panels a–c, the survey estimates are delimited by their corresponding period of reference and 95% bootstrapped confidence intervals. Median values are plotted as dashed horizontal lines. UN IGME (2025) estimates are plotted using the reported central tendency and 90% uncertainty bounds for each year. Panels d–f show bootstrapped distributions of the survey estimates. Median values are plotted as dashed vertical lines under the kernel density function, and 2.5th and 97.5th percentiles are shown as solid vertical lines on either side of each distribution. The distribution of Brass estimates corresponds to the period 2013–2018, and the central tendency and uncertainty bounds of the UN IGME (2025) estimate correspond to the year 2020.

several months. The bottom row of Figure 2 (panels d–f) compares the bootstrapped distribution of each data source. UN IGME estimates are represented by the point estimate and uncertainty bounds. Figure 2 includes RaMMPS estimates after poststratification, and both poststratified (weighted) and biased (unweighted) estimates are presented in tabular form in Table 4.

RaMMPS FPH estimates for the IMR of 40.32 per 1,000 (95% CI: 32.10–49.28) and the U5MR of 48.58 per 1,000 (95% CI: 39.61–57.97) are well-aligned with DHS VII, MICS 6, and UN IGME estimates. The FPH point estimate for the neonatal mortality rate, 30.98 per 1,000 (95% CI: 23.70–39.04), exceeds that of these external estimates, but uncertainty bounds overlap. RaMMPS TPH estimates are lower than the FPH estimates. For NMR, this implies that the TPH estimate of 21.04 per 1,000 (95% CI: 14.80–27.93) reproduces the UN IGME estimate for 2020.5–20.26 per 1,000 (90%

CI: 12.88–30.61)—but the IMR of 22.09 per 1,000 (95% CI: 15.70–29.28) and the U5MR of 24.84 per 1,000 (95% CI: 17.98–32.49) are noticeably lower than the estimates derived from the RaMMPS FPH module as well as the estimates from external sources. Indirect estimates of infant and under-five mortality—from the RaMMPS SBH module—correspond to UN IGME estimates. As discussed earlier, SBH estimates for the years immediately preceding the survey are unreliable and have been censored in 2018.

Sex and Time Variation of Under-Five Mortality in Malawi

Figure 3 further disaggregates model estimates of the RaMMPS FPH by period, making a comparison with estimates from DHS VII, MICS 6, and UN IGME. Coefficients and predicted probabilities of dying are reported in tabular form in Tables A1 and A2, respectively.

The most important takeaway points from Figure 3 can be summarized as follows. First, the period 2018.0–2020.0 is characterized by significantly lower mortality than the two adjacent periods. This fluctuation suggests either a downward bias from 2018.0 to 2020.0 or a reversal from 2020.0 to 2022.0 that nullified the mortality reductions between 2014.0 and 2020.0. Second, the magnitude and significance of this possible reversal are amplified by the use of poststratification weights. Third, the lowest mortality rate is predicted for the closing period 2022.0–2023.6. Although the statistical uncertainty around these estimates is important, point estimates derived from the RaMMPS FPH are indicative of declining mortality between 2014.0 and 2020.0. Most notably, RaMMPS FPH estimates suggest a reversal from 2020.0 to 2022.0, that is, the years mostly affected by the COVID-19 pandemic. However, it must also be noted that the uncertainty bounds of FPH estimates overlap and the precision of these period-specific estimates remains low.

Table 5 reports direct estimates and model predictions of the sex ratio of neonatal, infant, and under-five mortality rates by survey instrument, before and after using poststratification weights. The table also includes DHS estimates disaggregated by mobile ownership. Predicted ratios are estimated from (1) all regression coefficients, quantifying the departures from the overall mortality schedule, and accounting for the sex variation in the proportion of exposure that boys and girls are contributing to each period of reference; and (2) just the regression coefficient that is capturing the overall excess of male mortality and assuming the same mortality schedule, as previously described by Eq. (4).

According to Table 5, both direct estimates and model predictions of the sex ratio of under-five mortality in Malawi RaMMPS TPH are higher than in the DHS VII or the MICS 6. However, the CIs suggest sizable uncertainty around these estimates. RaMMPS FPH ratios are aligned with external sources, but the suggested excess of male mortality decreases after poststratification and is not statistically significant (i.e., confidence intervals include 1). Note that this is also the case with external sources. Ratios of under-five mortality indicate a significant excess of male mortality for a sample of all women 18–49, but not for the subsample of mobile users. In most

Table 4 RaMMPS, DHS, and UN-IGME estimates of the neonatal mortality rate (NMR), infant mortality rate (IMR), and under-five mortality rate (U5MR)

	NMR: $q(28d)$		IMR: $q(12m)$		U5MR: $q(60m)$	
Instrument	Poststrat.	Selected	Poststrat.	Selected	Poststrat.	Selected
TPH, 2014.0–2023.6	21.04 [14.80, 27.93]	20.33 [13.38, 27.91]	22.09 [15.70, 29.28]	21.00 [14.08, 28.78]	24.84 [17.98, 32.49]	24.22 [16.58, 32.66]
FPH, 2014.0–2023.6	30.98 [23.70, 39.04]	29.17 [21.40, 37.68]	40.32 [32.10, 49.28]	36.59 [27.52, 46.28]	48.58 [39.61, 57.97]	43.56 [33.77, 53.90]
SBH						
Brass: North, 2008.0–2013.0			65.64 [55.02, 88.23]	70.60 [47.84, 114.55]	102.08 [83.29, 142.44]	110.78 [70.57, 188.78]
Brass: North, 2013.0–2018.0			53.47 [48.34, 58.39]	48.87 [41.73, 62.43]	80.56 [71.51, 89.24]	72.39 [59.84, 96.44]
DHS VII, 2010.9–2015.9						
Women aged 15–49	26.29 [23.14, 29.56]		41.36 [37.45, 45.38]		62.44 [57.70, 67.24]	
Women aged 18–49	25.38 [22.31, 28.50]		40.09 [36.23, 43.89]		61.21 [56.58, 65.98]	
Women aged 18–49, mobile owners	23.00 [17.37, 29.44]	25.59 [19.72, 32.10]	37.71 [30.38, 45.91]	38.12 [30.92, 45.97]	59.72 [50.30, 70.34]	58.24 [49.45, 67.90]
MICS 6, 2015.2–2020.2						
Women aged 15–49	20.27 [17.18, 23.55]		37.84 [33.53, 42.48]		58.05 [52.58, 63.96]	
Women aged 18–49	20.54 [17.40, 23.88]		38.25 [33.89, 42.95]		58.47 [52.96, 64.42]	
Women aged 18–49, mobile owners	25.86 [18.43, 34.35]	22.56 [17.22, 28.58]	41.14 [31.82, 51.93]	36.85 [29.78, 44.94]	69.00 [55.98, 83.59]	60.01 [50.62, 70.40]
UN IGME, 2020.5	20.26 [12.88, 30.61]		32.26 [20.85, 48.27]		43.09 [27.85, 64.47]	
UN IGME, 2021.5	19.78 [12.06, 31.37]		31.40 [19.43, 49.22]		41.53 [25.70, 65.10]	

Table 4 (continued)

	NMR: $q(28d)$		IMR: $q(12m)$		U5MR: $q(60m)$	
Instrument	Poststrat.	Selected	Poststrat.	Selected	Poststrat.	Selected
UN IGME, 2022.5	19.33 [11.36, 32.03]		30.54 [18.08, 50.05]		39.94 [23.65, 65.47]	
UN IGME, 2023.5	18.83 [10.68, 32.62]		29.36 [16.78, 49.99]		38.34 [21.91, 65.28]	

Notes: Values are the median of a bootstrapped distribution, and the 2.5th and 97.5th percentiles are shown in square brackets. RaMMPS estimates are reported by survey instrument, and before and after poststratification weighting. DHS VII and MICS 6 estimates are for all women of reproductive age, women aged 18–49, and the subset of mobile phone owners (with and without using poststratification weights). UN IGME (2025) reports 90% uncertainty bounds. RaMMPS = Malawi Rapid Mortality Mobile Phone Survey. NMR = neonatal mortality rate. IMR = infant mortality rate. U5MR = under-five mortality rate. SBH = Summary Birth Histories. TPH = Truncated Pregnancy Histories. FPH = Full Pregnancy Histories. Poststrat. = poststratified.

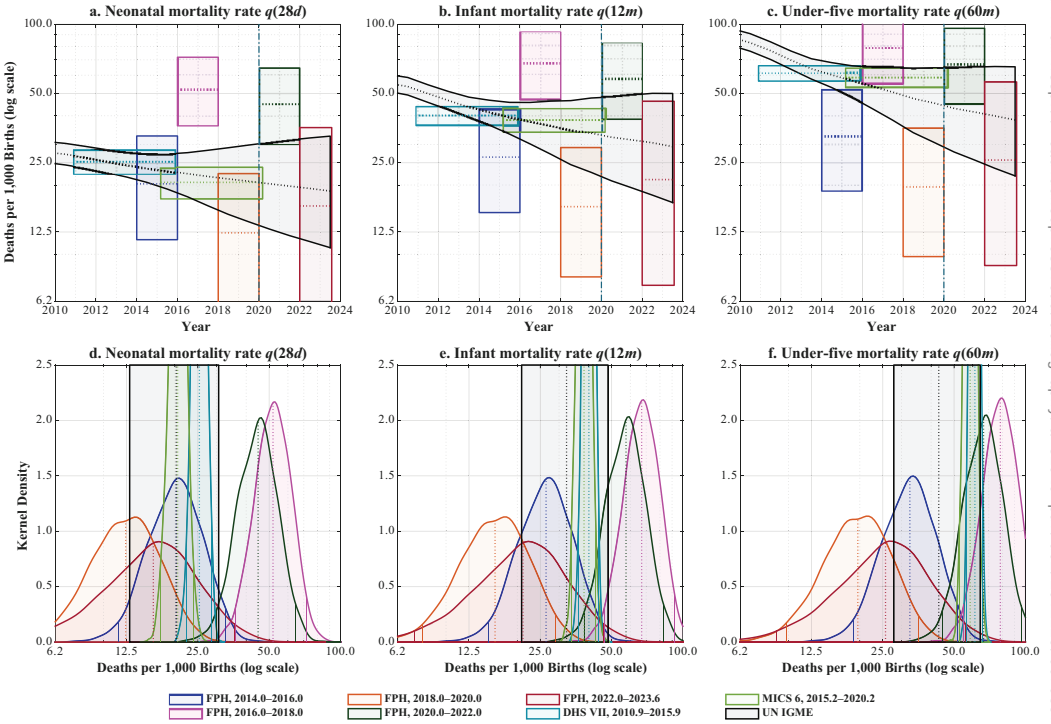

Fig. 3 Levels and distributions of the neonatal, infant, and under-five mortality rates from RaMMPS poststratified FPH by periods of reference. In panels a–c, the survey estimates are delimited by their corresponding period of reference and 95% credible intervals for the RaMMPS estimates—fitting a Poisson likelihood to the observed mortality rates by means of a Hamiltonian Markov chain Monte Carlo estimation—and 95% bootstrapped confidence intervals in the case of the DHS VII and MICS 6 estimates. Whether derived from a posterior or a bootstrapped distribution, median values are plotted as dashed horizontal lines. UN IGME (2025) estimates are plotted using the reported central tendency and 90% uncertainty bounds for each year. Panels d–f show the posterior or the bootstrapped distribution of each survey estimate. Median values are plotted as dashed vertical lines under the kernel density function, and 2.5th and 97.5th percentiles are shown as solid vertical lines on either side of each distribution. The central tendency and uncertainty bounds of the UN IGME (2025) estimate correspond to the year 2020.

cases, predicted sex ratios—imposing some control over the age pattern of U5M—could exhibit slightly less dispersion (i.e., narrower 95% percentile range), but the uncertainty of these estimates remains very high. This finding is partially related to the relatively small sample and the uneven distribution of boys and girls over the period of analysis. In a more comparable scenario in which all under-five individuals were contributing with the same proportion of exposure to the same periods of reference—and they were only different by sex, as indicated by Eq. (4)—predicted FPH ratios would be lower but not necessarily closer to those directly calculated from the DHS. Hence, owing to the small sample and the resulting sex imbalances over time, direct or model calculations of under-five mortality rates by sex are not advised using the Malawi RaMMPS.

Table 5 Direct estimates and model predictions of the sex ratio of under-five mortality metrics by survey instrument and source (with and without using poststratification weights)

	NMR: $q(28d)$		IMR: $q(12m)$		U5MR: $q(60m)$	
Instrument	Poststrat.	Selected	Poststrat.	Selected	Poststrat.	Selected
TPH, 2014.0–2023.6						
Direct estimation	6.19 [2.78, 22.05]	2.21 [1.06, 5.60]	6.56 [2.96, 23.17]	2.33 [1.11, 5.84]	5.75 [2.75, 18.38]	2.43 [1.19, 5.68]
Predicted: Poisson regression	5.93 [2.75, 15.85]	2.49 [1.26, 5.20]	5.92 [2.75, 15.85]	2.49 [1.26, 5.20]	5.97 [2.76, 16.03]	2.50 [1.26, 5.22]
Predicted: Poisson, via Eq. (4)	6.61 [3.12, 17.47]	2.55 [1.29, 5.24]	6.60 [3.11, 17.38]	2.55 [1.29, 5.24]	6.56 [3.11, 17.23]	2.54 [1.29, 5.21]
FPH, 2014.0–2023.6						
Direct estimation	1.08 [0.63, 1.81]	1.64 [0.91, 3.17]	1.22 [0.78, 1.91]	1.58 [0.94, 2.76]	1.15 [0.77, 1.72]	1.44 [0.90, 2.40]
Predicted: Poisson regression	1.13 [0.74, 1.76]	1.44 [0.92, 2.28]	1.14 [0.75, 1.77]	1.44 [0.92, 2.27]	1.14 [0.75, 1.77]	1.44 [0.92, 2.27]
Predicted: Poisson, via Eq. (4)	1.10 [0.72, 1.72]	1.39 [0.89, 2.18]	1.10 [0.72, 1.72]	1.38 [0.89, 2.17]	1.10 [0.72, 1.71]	1.38 [0.89, 2.17]
DHS VII, 2010.9–2015.9						
Women aged 18–49	1.59 [1.25, 2.04]		1.43 [1.19, 1.73]		1.30 [1.12, 1.51]	
Women aged 18–49, mobile owners	1.56 [0.92, 2.74]	1.59 [0.98, 2.71]	1.38 [0.91, 2.09]	1.44 [0.98, 2.14]	1.30 [0.93, 1.82]	1.28 [0.93, 1.75]
MICS 6, 2015.2–2020.2						
Women aged 18–49	1.69 [1.26, 2.25]		1.48 [1.16, 1.89]		1.30 [1.07, 1.59]	
Women aged 18–49, mobile owners	1.24 [0.65, 2.29]	1.36 [0.83, 2.24]	1.21 [0.75, 1.95]	1.36 [0.92, 2.03]	0.94 [0.63, 1.42]	1.05 [0.75, 1.47]

Notes: Values are the median, with 2.5th and 97.5th percentiles shown in square brackets, using either a bootstrapped distribution in the case of direct estimates or the posterior distribution of a Poisson–Hamiltonian Markov chain Monte Carlo for predicted estimates. NMR = neonatal mortality rate. IMR = infant mortality rate. U5MR = under-five mortality rate. TPH = Truncated Pregnancy Histories. FPH = Full Pregnancy Histories. Poststrat. = poststratified.

Discussion

In this contribution, we used data from birth and pregnancy histories collected via a mobile phone interview for estimating U5M in Malawi. Three survey instruments were used to that end: SBH, TPH, and FPH. In a related study, we extended these analyses to perinatal mortality (Reniers et al. 2025).

SBH capture the past trend of $q(12m)$ and $q(60m)$, but the quality of the Brass-type indirect estimates decreases, and the uncertainty bounds expand for estimates that are near the survey date. In addition, SBH impose strong assumptions about the age patterns of U5M and the regularity of the mortality changes over time. These restrictive assumptions make SBH not suitable for evaluating short-term mortality fluctuations.

The TPH and FPH instruments are adapted from instruments that have previously been used in face-to-face surveys fielded by the DHS program and can be used to produce direct mortality estimates. In the Malawi RaMMPS, women (aged 18–49) were randomly allocated to either one of those two instruments. The FPH instrument produces point estimates of $q(28d)$, $q(12m)$, and $q(60m)$ that are slightly higher than those published by the UN IGME, and these differences are more pronounced for the neonatal mortality rate. The uncertainty around our estimates remains relatively high, however, and this conclusion needs to be made with caution. The TPH instrument produces estimates that are lower than those from the FPH, as well as estimates from external sources. Again, this conclusion requires confirmation in a bigger sample but seems to corroborate an earlier analysis of comparing FBH estimates of U5M with those from TBH using survey data from the DHS Program (Masquelier et al. 2023).

Data from the FPH were also used to evaluate changes in U5M over time. These changes suggest a reversal in the U5M trend in 2020–2022. This possible mortality increase during the COVID-19 outbreak already manifested itself in $q(28d)$ and could be driven by changes in the utilization of health services in the antenatal and neonatal period, as suggested by other studies (Hekimoğlu and Aktürk Acar 2022). Some studies in Malawi showed that the COVID-19 pandemic was associated with increased maternal deaths, fewer postnatal care visits, neonatal inpatient admissions, nonsignificant changes in stillbirths and neonatal mortality, and community perceptions of increased mortality in general (Banda et al. 2025; Malla et al. 2023; Mndala et al. 2023). The uncertainty around these estimates is, however, large and this interpretation remains hypothetical. Regression analysis was conducted to quantify these time variations while keeping a number of other parameters constant, including the mortality age schedule and the sex ratio of under-five mortality. Regression coefficients are indicative of the same reversal. As expected, the male to female ratio of U5M exceeds one, but this difference fails to reach statistical significance.

Selection bias frequently poses a significant challenge in mobile phone surveys, particularly in contexts where mobile phone ownership is not widespread and may be correlated with mortality. To address this issue, we employed quota sampling with active monitoring of strata and applied poststratification weights to ensure that our sample better represents the sociodemographic characteristics of the target population. Since quotas were determined by the type of residence (urban/rural), applying poststratification weights had little effect on the mortality estimates, generally causing only a slight, nonsignificant upward adjustment. Another study, which compared

U5M estimates between owners and nonowners of mobile phones in the DHS, also suggested that the selection bias would be relatively small for Malawi (Sánchez-Páez et al. 2023). That study evaluated only selection bias associated with the sampling frame and did not account for bias resulting from selective nonresponse.

Even though our results suggest that U5M can be reliably estimated in an MPS, and particularly so with the FPH survey instrument, selection bias may be more pervasive and less tractable for other demographic indicators. This is the case for indicators of fertility, where estimates remain biased downward, even after the application of poststratification weights. Again, this result corroborates an earlier study that compared fertility estimates of owners and nonowners of mobile phones from the DHS (Sánchez-Páez et al. 2023) and could be due to the fact that fertility is an expression of preferences not fully captured by the poststratification variables that we used.

Conclusion

MPS can be a useful method for gathering U5M data in settings where civil registration is insufficiently reliable to produce timely and unbiased mortality estimates. MPS can be deployed rapidly in crisis situations, where face-to-face data collection is hindered and up-to-date public health data are of critical importance to inform health policy responses. The most promising of the three survey instruments that we tested is the Full Pregnancy Histories. In comparison, Summary Birth Histories are briefer to administer and produce estimates that are comparable to those published by external sources—but estimates are dated and rest on a number of assumptions that cannot be tested. As documented elsewhere, Truncated Pregnancy Histories tend to produce estimates that are biased downward (Masquelier et al. 2023). Our study is one of the first attempts to collect survival data via mobile phones and to randomize different survey instruments. Our promising results should encourage demographers to test this approach in other contexts—where face-to-face surveys are impossible for logistical or financial reasons. For example, in humanitarian contexts, mortality is often calculated with a quick module on deaths in the household over the last few months (Working Group for Mortality Estimation in Emergencies 2007), but these questions do not measure age-specific mortality (e.g., neonatal, infant, under-five) and do not capture time trends.

Selection bias is inherent to MPS in the sense that mobile phone ownership is unequally distributed and often correlated with many of the outcomes of interest. This is also the case for U5M mortality, but our results indicate that this bias can be overcome by imposing sampling quotas and applying poststratification weights. Whereas this strategy appears to work well for U5M indicators, we acknowledge that this may not be the case for other demographic measures, including the TFR. Possibly this is due to the fact that fertility, unlike mortality, is less directly a function of a mother's attributes and living conditions but also an expression of fertility preferences that are not typically captured by the poststratification variables (Sánchez-Páez et al. 2023). ■

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Reproducibility and Data Availability Code is provided at https://github.com/Romero-Prieto/RaMMPS_U5M, where the availability of raw data files is also described.

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