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Clustering of child deaths among families in low and middle-income countries: A meta-analysis

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Abstract

Background and Aims: Several studies have examined the phenomenon of "death clustering," in which two or more children born to the same mother or from the same family die at an early age. Therefore, a scientific examination of the results is essential to understand how the survival status of the older siblings affects the survival of the younger siblings. By using meta-analysis, this study aims to provide a quantitative synthesis of the results of studies on "child death clustering" in low- and middle-income countries (LMICs).

Methods: This study followed the PRISMA-P 2015 guidelines. We used four electronic databases—PubMed, Medline, Scopus, and Google Scholar with search and citation analysis capabilities. Initially, 140 studies were identified, but only 27 met the eligibility criteria eventually. These were studies that had used the death of a previous child as a covariate to determine the survival status of the index child. The heterogeneity and the publication bias of the studies were examined using the Cochran test, I^2 statistic, and Egger's meta-regression test.

Results: The pooled estimate of 114 study estimates for LMICs contains some bias. India's 37 study estimates were distributed more or less equally along the middle line, indicating no publication bias, while there was a slight bias in the estimates for Africa, Latin America, and Bangladesh. The odds of experiencing the death of the index child in the selected LMICs were 2.3 times higher for mothers who had lost any prior child as compared to those mothers who had not had any prior child loss. For African mothers, the odds were five times higher, whereas for Indian mothers, the odds were 1.66 times higher. Mothers' characteristics, such as education, occupation, health-seeking behavior, and maternal competence, significantly affect the child's survival status.

Conclusion: Achieving the sustainable development goals would not be possible if mothers in countries experiencing high levels of under-five mortality are not provided with better health and nutrition facilities. Mothers who have lost multiple children should be targeted for assistance.

KEYWORDS
child death clustering, child mortality, India, low- and middle-income countries, meta-analysis, PRISMA-P

1 | INTRODUCTION

Child mortality estimates are a significant indicator of the overall development of a country/region. In 2019, two regions-sub-Saharan Africa and Central and Southern Asia-accounted for over 80% of under-five deaths. Sub-Saharan Africa had the highest neonatal mortality rate with 27 deaths per 1000 live births (95% CI [25, 32]),[1] followed closely by Central and Southern Asia with 24 deaths per 1000 live births (95% CI: [22–26]).[2] The global efforts to reduce child mortality face a potential threat from the phenomenon of "child death clustering."[3]

Clustering of family deaths has been observed in both historical and contemporary populations. "Child death clustering" occurs when a small proportion of mothers/families experience a disproportionately large number of child deaths. This paper uses the term family interchangeably with the term woman. Around 25 years ago, Monica Das Gupta became the first researcher to recognize a pattern of child death clustering among specific subgroups of families in the Indian region.[4,5] In recent years, several studies have addressed the issue of mortality clustering. A child's death increases the risk of death for their next sibling, a phenomenon known as scarring effect or state dependency in literature. Studies have demonstrated that death clustering remains significant even after adjusting for mother-level factors such as birth spacing and mothers' education. However, the contribution level of the factors seems to differ among different populations.[6–8]

There are studies which have adjusted unobserved heterogeneity like genetic traits or maternal ability as also observed household and community characteristics in the regression model and have concluded that the survival status of an older sibling predicts the risk of death of the subsequent child.[3,6,9–17] There are several pathways through which the scarring effect may occur. For instance, it may occur if a mother wishing to replace the dead child[18,19] and resumes fecundity soon after the death of the infant and conceives again[20,21] which may result in the loss of the subsequent child.[9] The scarring effect may also occur when an infant's death causes depression in the mother, which may seriously affect the infant born later either after birth or while still in the womb.[22,23]

The importance of the scarring factor, measured by the coefficient of previous child death as an independent covariate in the regression model, is well documented in demographic literature.[8,11,12,14,16,17,24] This coefficient has been considered in our analysis as well. The scarring effect varies from study to study and varies at the country as well as at the subnational and subgroup levels. Using meta-analysis for each low- and middle-income country can provide robust results that can help researchers and policy planners better understand the magnitude of past child deaths. The use of meta-analysis provides policy planners vital clues that were not previously available. In a meta-analysis, we consider the coefficient of the survival status of an older sibling in a family. Typically, this independent variable is a lagged variable that captures the clustering effect of child mortality in most studies. Statistically significant coefficients of previous child deaths indicate the presence of clustered child deaths at the family level for a particular region.

This study aims to provide a quantitative synthesis of the results of studies on "child death clustering" in low- and middle-income countries (LMICs) and also attempts to explore the unobserved and observed factors contributing to child death clustering within families.

2 | METHODS

To achieve the objectives of the study, we used PRISMA-P 2020 or "Preferred reporting items for systematic review and meta-analysis protocols" .[25,26] We analyzed 27 studies from 16 LMICs in Asia (India and Bangladesh), Africa (Malawi, Benin, Ghana, Côte d'Ivoire, Senegal, Cameroon, Kenya, Rwanda, Egypt, Morocco, Sudan, and Tunisia), and Latin America (Guatemala and Brazil) to estimate "death clustering". All odds ratios reported at the national and subnational levels were considered independent to determine the pooled estimate of the clustering effect on child mortality.

Searches for relevant articles on death clustering of children under five were conducted on PubMed, Medline, Scopus, and Google Scholar. The searches looked for three outcome variables neonatal, infant, and under-five child deaths as well as for studies that included older siblings as covariates. Articles written in English from 1990 through 2022 were searched between September 18, 2015 and August 10, 2022, and the outputs were managed using EndNote. Before screening the studies for eligibility, duplicate records were removed. Two authors extracted the data independently using a preagreed data abstraction template. Disparities between authors were resolved by consensus before involving a third and a fourth author. The primary outcome covariate for the meta-analysis was previous child death (neonatal or infant or under-five death). Previous child death was a lagged variable generated at the family (mother) level in different studies for index child survival status and was adjusted in the model as one of the covariates.

The following information was extracted for the study: citation, author name & year of publication, country or regional setting, sample size, estimation methods, sampling methods, models, covariates, data type (longitudinal or cross-sectional), outcome measure, clustering variable, clustering variable estimate, use of previous child

death as a covariate in the model, and inclusion of unobserved variation at the mother level in the model.

We present here the results of the searches conducted exclusively on Medline. Similar searches were also conducted in the other databases. The studies were searched using a combination of operators such as AND, OR, and so forth, as used in advanced searches in this database: ((((((((((Death) AND (clustering)) AND (English[Language])) OR (infant mortality clustering [MeSH Major Topic])) OR (Neonatal mortality clustering [MeSH Major Topic])) OR (Under 5 child mortality clustering [MeSH Major Topic])) OR (Infant death clustering [MeSH Major Topic])) OR (Neonatal death clustering [MeSH Major Topic])) OR (Under 5 death clustering [MeSH Major Topic])) OR (sibling survival [All Fields])) OR (previous deaths [All Fields])) OR (Family clustering)) OR (Familial clustering).

We assessed the risk of bias of each study at three levels: study, covariate, and outcome. Two of the authors used the following quality assessment criteria to evaluate each study: (1) Definitions of previous child deaths, (2) Outcomes measured; definitions for neonatal, infant, and under-five child mortality, (3) Completeness of information regarding previous child deaths, (4) Completeness of the outcome measures, (5) Completeness of ascertainment of live births, (6) Sampling technique/design, and (7) Data quality. Based on each criterion, the studies were rated as "high risk of bias" or "low risk of bias." The risk of bias was assessed for model-based estimations based on the input data.

As shown in Figure 1, the literature search identified 140 studies to begin with. Of them, 20 were found to be duplicate and, therefore, removed. The remaining 120 studies were screened for eligibility

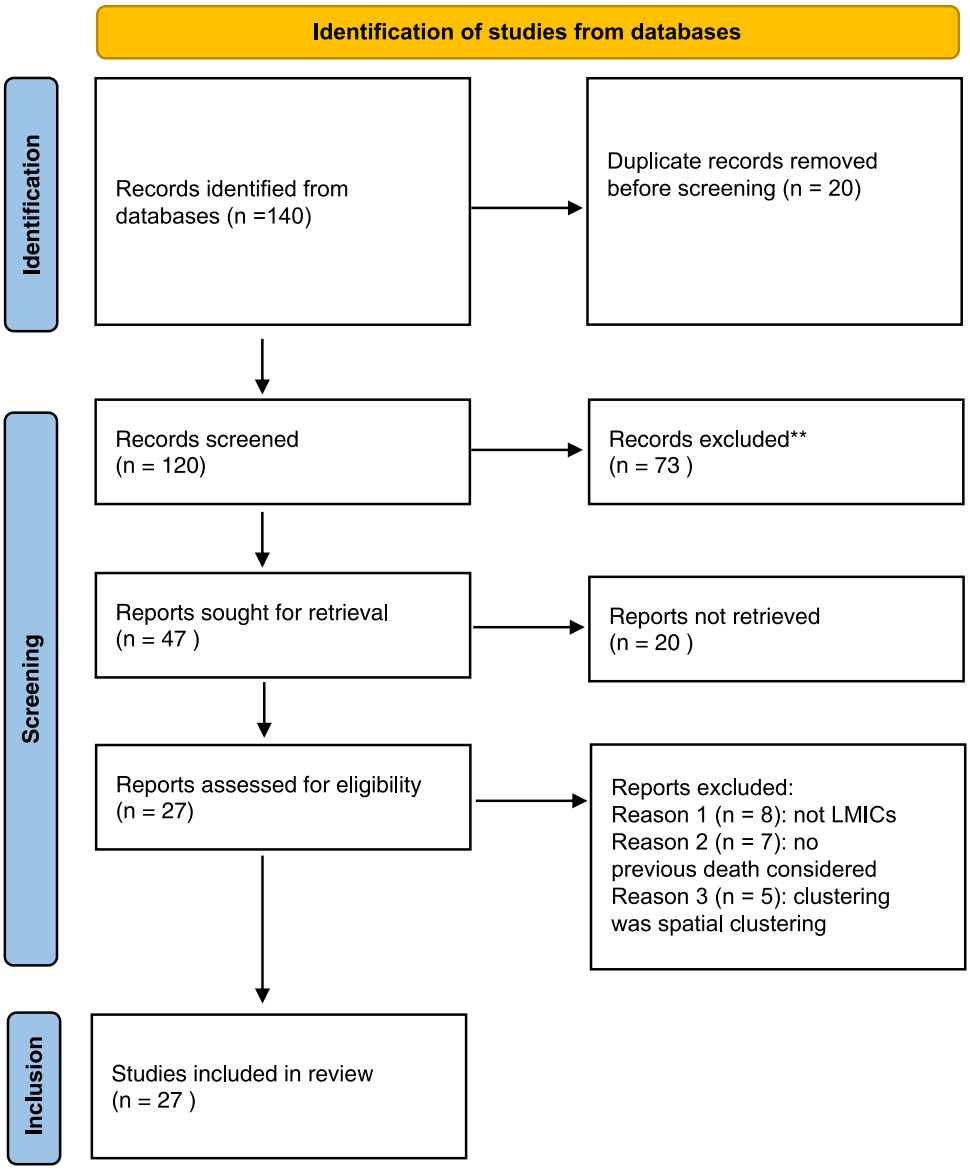

FIGURE 1 Flow chart of study selection for inclusion in the meta-analysis (PRISMA 2020 statement: an updated guideline). *Source*: Page MJ, McKenzie JE, Bossuyt PM et al.[41] LMIC, low- and middle-income countries.

TABLE 1 Risk of bias in individual studies.

No	References	Definitions of outcomes measured and of previous child deaths	Ascertainment of deaths/live births	Sampling technique/ design	Data quality	Overall risk of bias
1	Arulampalam et al.[10]	Low	Low	Low	Low	Low
2	Arulampalam et al.[9]	Low	Low	Low	Low	Low
3	Bhalotra et al.[27]	Low	Low	Low	Low	Low
4	Das Gupta[4]	Low	Low	Low	Low	Low
5	Dwivedi et al.[28]	Low	Low	Low	Low	Low
6	Ranjan et al.[17]	Low	Low	Low	Low	Low
7	Ranjan et al.[29]	Low	Low	Low	Low	Low
8	Meitei et al.[30]	High	Low	Low	Low	High
9	Paul et al.[31]	High	Low	Low	Low	High
10	Srivastava et al.[32]	High	Low	Low	Low	High
11	Srivastava et al.[33]	High	Low	Low	Low	High
12	Saha et al.[24]	Low	Low	Low	Low	Low
13	Majumder et al.[34]	Low	Low	Low	Low	Low
14	Nonyane et al.[35]	Low	Low	Low	Low	Low
15	Zenger[7]	Low	Low	Low	Low	Low
16	Paul et al.[36]	High	Low	Low	Low	High
17	Guo[11]	Low	Low	High	Low	High
18	Guo et al.[12]	Low	Low	High	Low	High
19	Sastry[13]	Low	Low	Low	Low	Low
20	Defo et al.[37]	Low	Low	Low	Low	Low
21	Manda[14]	Low	Low	Low	Low	Low
22	Omariba et al.[38]	Low	Low	Low	Low	Low
23	Omariba et al.[15]	Low	Low	Low	Low	Low
24	Madise et al.[39]	High	Low	High	Low	High
25	Bolstad et al.[40]	Low	Low	Low	Low	Low
26	Omariba et al.[16]	Low	Low	Low	Low	Low
27	Akinyemi et al.[3]	Low	Low	Low	Low	Low

based on their titles and abstracts. This resulted in the exclusion of 73 studies and the shortlisting of 47 abstracts for a full-text review. Finally, only 27 studies met the eligibility and inclusion criteria for further analysis. All 27 studies had used previous child deaths as a covariate. The flow chart used in the study is based on PRISMA 2020 statement: an updated guideline.[41] The study characteristics for child death clustering data are presented in Table 2, while the risk of bias in specific studies is shown in Table 1.

The statistical analysis was conducted using STATA Ver. 17. The selected studies were used to estimate the pooled or combined odds ratio and their standard errors. The Cochran heterogeneity test was applied to show the significant difference between the study variation in the outcomes ($p < 0.000$), whereas the I^2 statistic was calculated to measure the degree of consistency. I^2 statistic describes the percentage of total variation across studies due to heterogeneity rather than chance.[42,43] Forest and Funnel Plots were used to visualize the results of the meta-analysis and to assess publication bias. The asymmetry of the funnel plot was tested using Egger's meta-regression test. A regression analysis of Galbraith's radial plot was conducted to assess funnel plot asymmetry in various regions. p Values of 0.05 and below were considered statistically significant.

TABLE 2 Characteristics of studies that measured child death clustering.

No	References	Duration covered	Definitive empirical data source	Design	Estimation (previous child death) based on model
1	Arulampalam et al.[10]	1968–1999	NFHS-2 (secondary)	Population based survey	Dynamic random-effects logit model
2	Arulampalam et al.[9]	1968–1999	NFHS-2 (secondary)	Population based survey	Dynamic random-effects logit model
3	Bhalotra et al.[27]	1968–2000	NFHS-2 (secondary)	Population based survey	Dynamic random-effects logit model
4	Das Gupta[4]	1984–1987	Primary survey data	Prospective study births	Logit regression model
5	Dwivedi et al.[28]	1970–2006	NFHS-3 (secondary)	Population based survey	Dynamic random-effects logit model
6	Ranjan et al.[17]	1970–2007	NFHS-3 (secondary)	Population based survey	Multilevel random effects logit model
7	Ranjan et al.[29]	1970–2016	NFHS-4 (secondary)	Population based survey	Bayesian geoadditive model
8	Meitei et al.[30]	1970–2016	NFHS-4 (secondary)	Population based survey	Weibull hazard model with gamma shared frailty
9	Paul et al.[31]	1970–2016	NFHS-4 (secondary)	Population based survey	Two-level random intercept weibull regression model
10	Srivastava et al.[33]	1970–2016	NFHS-4 (secondary)	Population based survey	Random-intercept logit models
11	Srivastava et al.[32]	1970–2016	NFHS-4 (secondary)	Population based survey	Cox proportional hazards model
12	Saha et al.[24]	1977–1998	Health & surveillance system data (secondary)	Intervention & control type	Dynamic random-effects logit model
13	Majumder et al.[34]	1959–1989	Bangladesh fertility survey (secondary)	Population based survey	Logit regression model
14	Nonyane et al.[35]	2001–2005	Projahnmo-Sylhet study (primary)	Cluster randomized controlled	Random effect logistic model
15	Zenger[7]	1970–1982	Demographic surveillance system (secondary)	Longitudinal survey data	Generalized estimating equations
16	Paul et al.[36]	2017–2018	Bangladesh DHS (secondary)	Population based survey	Gompertz frailty regression model
17	Guo[11]	1974–1976	INCAP-RAND Guatemala survey (secondary)	Population based survey	Standard hazards proportional model, multiplicative gamma frailty model, multiplicative nonparametric frailty model
18	Guo et al.[12]	1974–1977	INCAP-RAND Guatemala survey (secondary)	Population based survey	Standard hazards proportional model, multiplicative gamma frailty model, multiplicative nonparametric frailty model
19	Sastry[13]	1976–1986	Brazil DHS (secondary)	Population based survey	Multilevel proportional hazards model
20	Defo et al.[37]	1970–1990	WFS & DHS (secondary)	Population based survey	Logit regression model
21	Manda[14]	1986–1992	Malawi DHS (secondary)	Population based survey	Three level logistic model
22	Omariba et al.[38]	1984–1998	Kenya DHS (secondary)	Population based survey	Weibull standard model
23	Omariba et al.[15]	1984–1999	Kenya DHS (secondary)	Population based survey	Weibull frailty model
24	Madise et al.[39]	1973–1988	Malawi family formation survey (secondary)	Population based survey	Logistic binomial model
25	Bolstad et al.[40]	1987–1992	Malawi DHS (secondary)	Population based survey	Hazard model with family and community random effect
26	Omariba et al.[16]	1983–1998	Kenya DHS (secondary)	Population based survey	Lagged binary model
27	Akinyemi et al.[3]	1980–2013	Nigeria DHS (secondary)	Population based survey	Dynamic random effects model

3 | RESULTS

3.1 | Clustering of infant deaths

The studies included for the meta-analysis have cited various reasons for death clustering within families. Zaba and David argued that 'clustering' of deaths is due to systematic parity effects that expose children to fatalities.[44] The death of a previous child was found to be associated with the mortality risk of the index child in 11 studies.[7,8,10–12,15,16,24,33,36,45] According to a few studies conducted in India (including in Punjab[4,5] and Odisha[45]), Mali,[46] Guatemala,[11,12] Brazil,[6,13] Bangladesh,[7,24,34–36] Senegal,[8] Nigeria,[3] and Kenya,[3,15,16,38] survival chances are more or less similar between children born into the same family and those born into different families. Further, eight studies relied solely on bivariate analysis to account for women who had experienced more than one child loss and the extent of deaths clustered in these families.[4,5,8,13,17,28,44,45]

3.2 | Results of forest plot analysis

In Table 3, Figures 2 and 3, the pooled estimate of the impact of previous child mortality in families on the survival status of the index child is shown. The pooled estimate was significant (2.37,$P < 0.001$) for both Africa (5.49, $P < 0.001$) and India (1.66, $P < 0.001$). In contrast, it was insignificant for Bangladesh (1.27; $P > 0.10$) and Latin America (1.01; $P > 0.10$). Among families who had experienced child loss in the past, the odds of infant death in Africa were five times higher and in India, 66 percent higher as compared to those families who had not had any child loss. The pooled estimate under the random effects model was 2.37, showing that the odds of infant death were almost two and half times higher if families had experienced prior infant loss. The I^2 statistic was 99% for India and 98% for Africa, indicating that estimates were based on a heterogeneous set of studies.

3.3 | Funnel plot: Publication bias in the studies

Figure 3 illustrates the publication bias of the studies included in the meta-analysis for various regions. For India, all 37 study estimates were distributed more or less equally from the middle line, and the funnel was inverted, indicating no publication bias. Bangladesh, Latin America, and Africa had more asymmetric estimates, although the funnel was inverted. On the whole, there was a slight bias in the study estimates, which can be verified in future research. The pooled estimate of 114 study estimates for LMICs too contained some bias.

3.4 | Analysis of funnel plot asymmetry: Egger's test for small-study effect

The funnel plot assumes that studies with high precision will be plotted near the average without publication bias. An uneven funnel-shaped distribution will result if studies with low accuracy are evenly

TABLE 3 Result obtained from random effects model: Pooled estimates of previous infant deaths in families, test for heterogeneity, and I^2 statistic by countries and regions.

Regions of world	Pooled estimates of previous infant deaths	95% CI		Asymptotic z-value	P value	Number of studies	Test for heterogeneity: Q value (P value)	I^2 statistic
		Lower	Upper					
India								
Random	1.66	1.58	1.75	19.78	<0.001	66	9989.32 (<0.001)	99.3
Africa								
Random	5.16	4.29	6.20	17.49	−<0.001	30	1681.29 (<0.001)	98.3
Bangladesh								
Random	1.27	0.84	1.946	1.146	>0.10	9	336.72 (<0.001)	97.6
Latin America								
Random	1.01	0.88	1.17	0.19	>0.10	9	0.87 (>0.10)	0.001
All developing countries								
Random	2.37	2.22	2.53	26.47	<0.001	114	32,747.68 (<0.001)	99.7

Note: India* (pooled estimates are based on estimates from studies on states like Punjab, Uttar Pradesh, West Bengal, Kerala, Madhya Pradesh, Odisha, Bihar, Rajasthan, Haryana, Gujarat, Maharashtra, Andhra Pradesh, Karnataka, Tamil Nadu, North-east India, EAG (Empowered Action Group) states, Non-EAG states, urban and rural India, and India).

Bangladesh* (Sylhet, Mirzapur, and Bangladesh).

African* region countries (Kenya, Malawi, Benin, Ghana, Cote d'Ivorie, Senegal, Cameroon, Rwanda, Egypt, Morocco, North Sudan, Tunisia, and Nigeria).

Latin American* region countries (Guatemala and Brazil).

All developing countries* (All studies from India, Bangladesh, African region, and Latin American region).

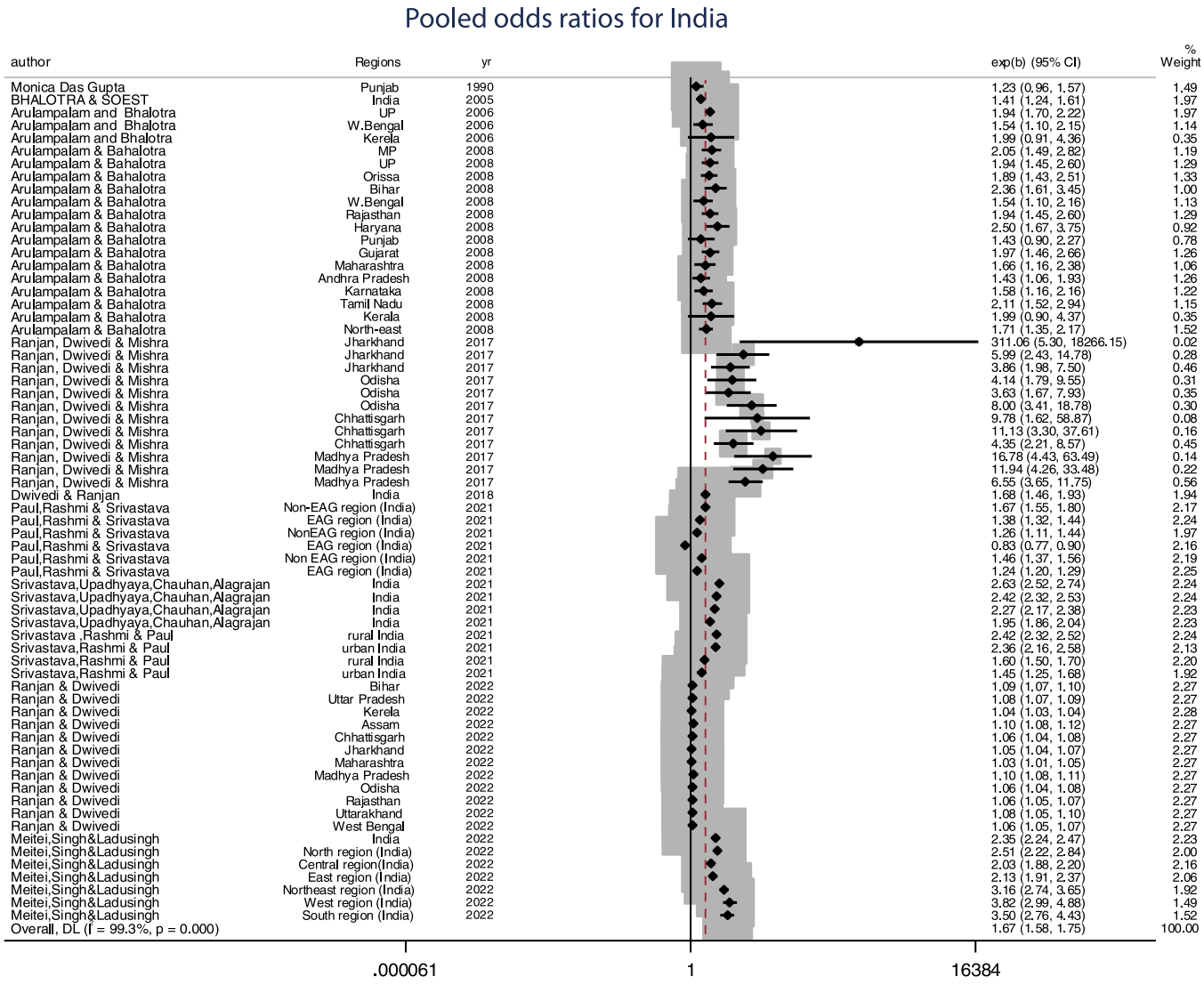

FIGURE 2 Pooled estimate based on forest plots for India and other developing regions of world.

distributed on both sides of the average. Therefore, in the absence of bias, random fluctuations should produce a symmetrical distribution of intercepts around a central value of zero with an equal number of positive and negative values. Table 4 shows the funnel plot asymmetry using regression analysis of Galbraith's radial plot. The results indicate that the bias was not significant for Africa, Bangladesh, and Latin America. In Figures 4 and 5, the funnel plot for the pooled estimate for all the selected LMICs and Africa indicates publication bias. Africa exhibited a more pronounced bias. The plots were more asymmetrical, with more points distributed on one side than on the other. An asymmetric funnel indicates the relationship between treatment effect estimates and study precision. It suggests the possibility of either publication bias or a systematic difference between studies of higher and lower precision. However, variations for all LMICs showed a negative deviation asymmetry and estimates were reported on the low side. The negative bias in the estimates for Africa and LMICs indicate that the smaller studies revealed more pronounced beneficial effects than the more extensive studies.

3.5 | Mother-level unobserved factors

Of the 27 studies, 10 had attempted to capture unobserved variation at the mother's level.[3,9,10,14,15,24,28,30,40,44] Most of these studies attributed the unobservable factors operating at the mother's level to genetic factors. In 1997, Narayan Sastry attempted to separate the community effect from unmeasured family frailty (genetic factors and parental competence).[13] Unmeasured factors include the much-discussed "maternal competence" factor, which refers to the mother's breastfeeding behavior and other attitudes that impact her child's health. Despite the importance of maternal competence in a child's care and survival, it has received only marginal attention due to measurement problems. However, two studies included in our meta-

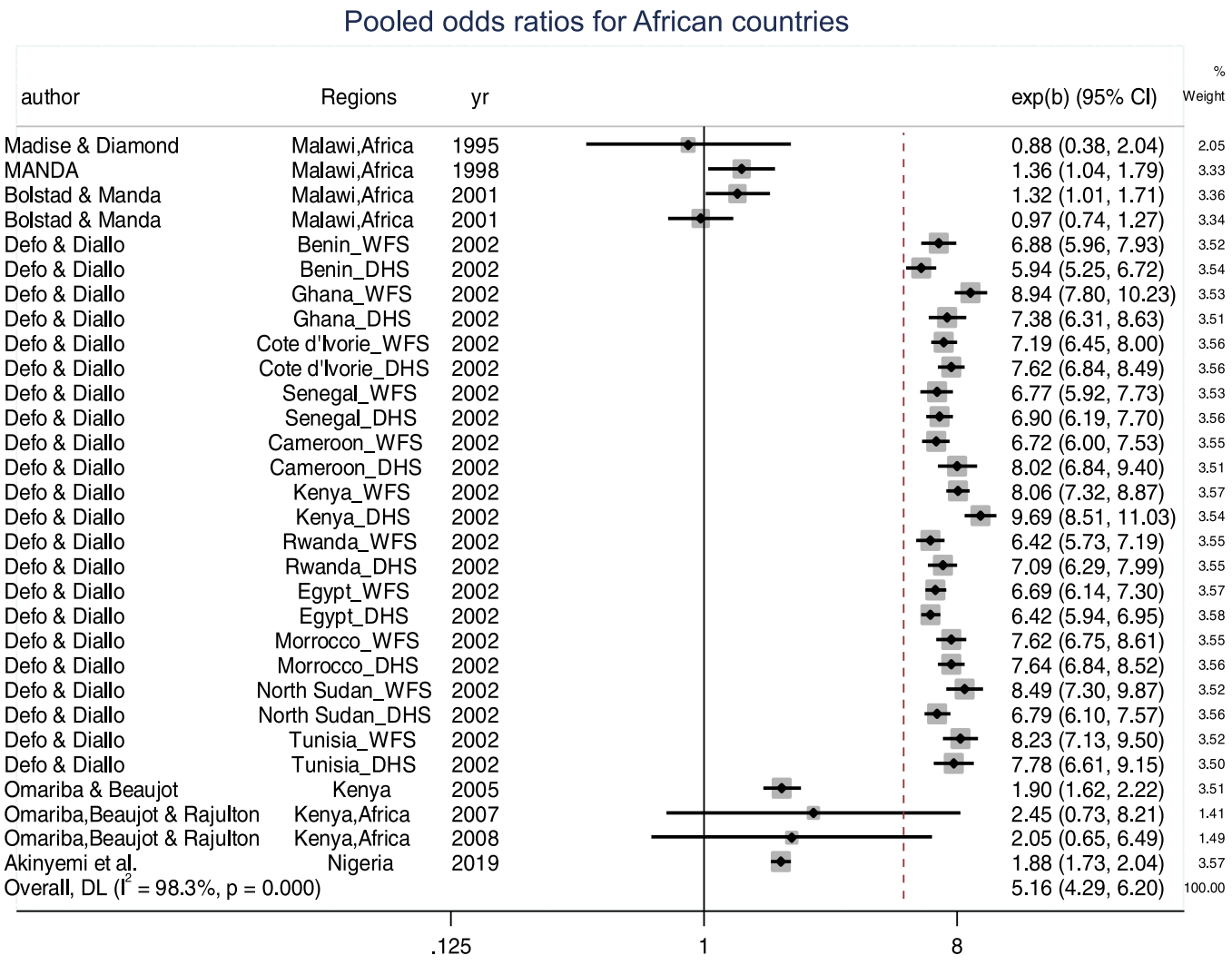

FIGURE 2 Continued

analysis were found to have attempted to gain insights into maternal competence factors through in-depth interviews.[4,45]

3.6 | Differentials in observed biodemographic characteristics of the families (mother)

Most studies had reported that families at high risk (those with two or more deaths) had poor outcomes in socioeconomic and biodemographic characteristics. Approximately half of the studies considered mother's age and its square term for linearity as significant biodemographic factors affecting the clustering of deaths in the family.[4,9–12,14,16,24,27,34] Only one study included the breastfeeding status of women as a factor affecting the survival status of the child.[12] Eight studies examined both birth order and birth interval as predictors of mortality clustering,[4,11,12,14,16,24,27,34] while 10 studies examined either birth order or birth interval as a predictor of mortality clustering. Genetic factors were acknowledged in five studies but were excluded from their models due to measurement issues.[4,5,34,39,45] On the other hand, 10 studies consistently argued that if the model did not include genetic factors, the coefficient of previous death, a measure of death clustering, would be overestimated.[7,9–11,14,15,17,24,29,30] Therefore, it is better to consider unobserved factors such as genetics and community-level factors that may affect the concentration of deaths within families.

3.7 | Differentials in observed socioeconomic characteristics of families/mothers

The variables that measure a family's socioeconomic status, such as occupation, social class, income, and level of education, also affect a child's health. Nine studies identified parents' educational status (either father's or mother's education or both) as an essential factor for calculating the risk of death of a child in families.[4,9,12,13,16,27,28,34,46] A total of 17 studies considered household religion, caste, and income as essential family-level factors for studying death clustering.[2,3,9–11,13,16,29,31–33,35–37,39,43–45]

FIGURE 2 Continued

4 | DISCUSSION

Most studies from LMICs other than India were restricted to African countries and Bangladesh. The pooled estimate indicates that infant deaths in Africa and India were higher in families with a history of infant loss. The studies revealed that the observed characteristics of the mother, like education, income, health-seeking behavior, and behavior toward child care (maternal competence), have relevance in explaining death clustering at the family level. The maternal competence factor was studied in two studies using semi-structured in-depth interviews in high-risk families.[5,45] According to these studies, if a woman ignores newborn care repeatedly, her child will die. Further studies have shown that the role of father's education can't be ignored. The basis for the argument favouring the inclusion of father's education lies in the fact that most of the household decisions related to contraceptive preferences and family size are made by the husband in many developing countries.[38,40] Also, in cases where the information related to income is not reported accurately, information on father's education acts as a correction factor.[39] Van Bodegom et al. in their study on the polygamous population of Ghana, found the role of the father in an environment like that to be significant in explaining death clustering within the family.[47] Regardless of the location of the studies, numerous studies have highlighted the greater importance of bio–demographic factors in explaining the extent of child mortality clustering than socio–economic and behavioral factors. It is also

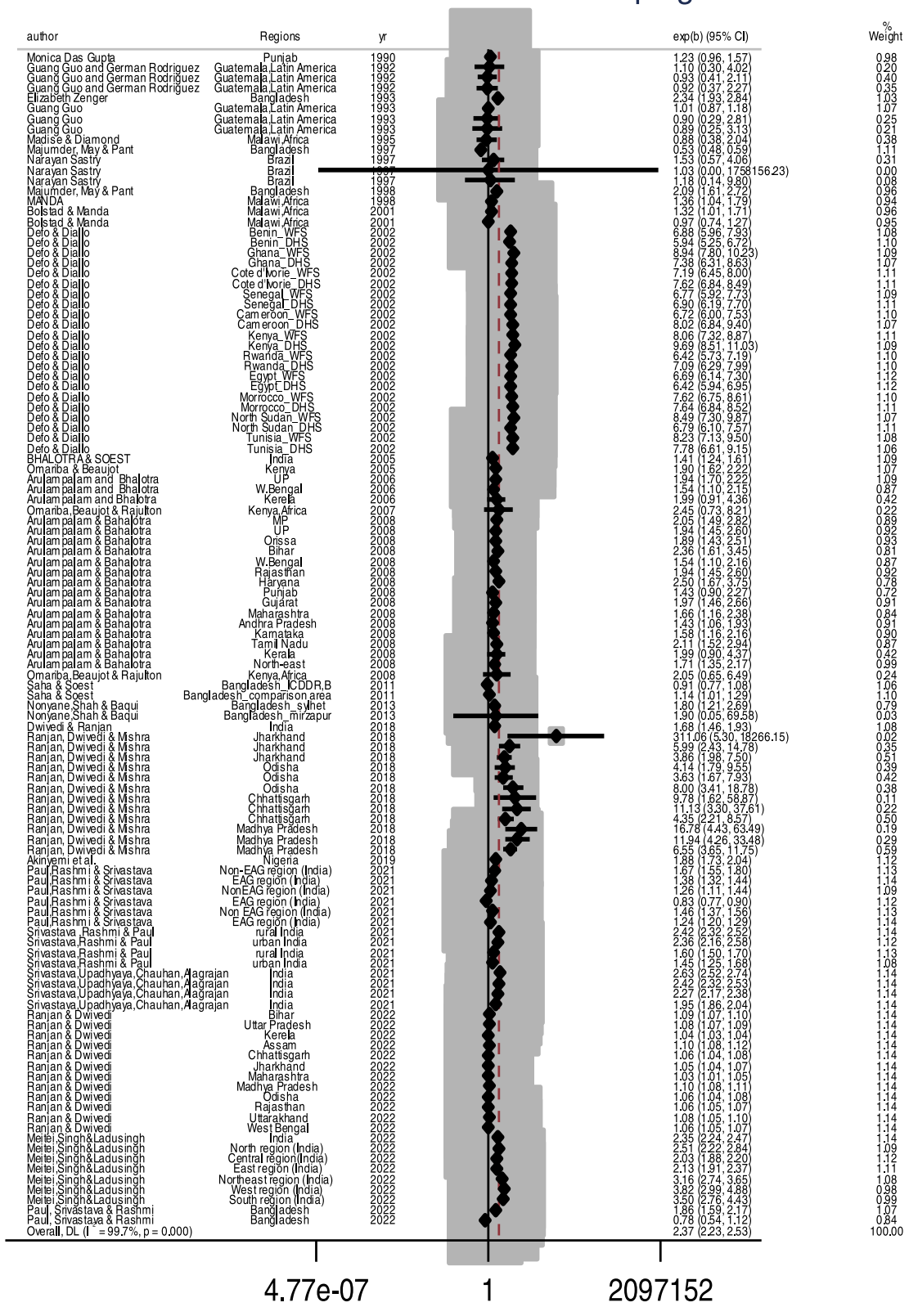

FIGURE 3 Pooled estimate based on forest plots for different developing countries of world.

TABLE 4 Results obtained from the analysis of funnel plot asymmetry through Egger's test for small-study effects by developing countries of various regions.

Regions of world	Bias	95% CI		t-value	P Value	Number of study estimates
		Lower	Upper			
India						
Slope	0.03	−0.01	0.06	1.88	<0.10	66
Bias	8.41	5.59	11.24	5.95	<0.001	
Africa						
Slope	2.04	1.56	2.52	8.64	<0.001	30
Bias	−3.96	−11.39	3.48	1.09	>0.10	
Bangladesh						
Slope	−0.39	−1.27	0.49	1.05	>0.10	9
Bias	5.24	−4.77	15.24	1.24	>0.10	
Latin America						
Slope	0.01	−0.07	0.09	0.25	>0.10	9
Bias	0.04	−0.31	0.39	0.28	>0.10	
All developing countries						
Slope	0.03	−0.02	0.07	1.22	>0.10	114
Bias	11.56	8.77	14.36	8.20	<0.001	

evident that even after controlling the significant covariates, unexplained variation at the mother level remains present in the model. This implies the relative significance of unobserved factors influencing the concentration of child deaths in families. Most studies in India measure the unobserved heterogeneity at the mother level as a measure of biological/genetic differences between mothers in the risk of experiencing child loss. Zenger, in her study, did not include unobserved heterogeneity existing at the mother level and the survival status of the preceding child in the model simultaneously.[7] A few subsequent studies tried to include both factors in the model, but they ignored the endogeneity bias because siblings of the same mothers share similar genetic characteristics and are correlated, violating the regression model's basic assumption.[11,13,40]

As a result, bias may exist in the estimates of the previous sibling's survival status in all of the studies. This problem was addressed by Arulampalam and Bhalotra in their work, in which they used a random effects dynamic model[9,10] to simultaneously capture the scarring effect (state dependence) as well as unobserved heterogeneity while also addressing the endogeneity problem by modeling the survival status of the first child with that of the mother-level random effects parameter or unobserved heterogeneity and a set of observed explanatory variables. Many studies found only modest or insignificant heterogeneity in explaining the risk of child death among families after adjusting covariates including unobserved factors.[11–13,16] On the other hand, a few studies also found the effect of mother-level unobserved factors to be stronger[10,13,24,35] in explaining clustering.

In the past, demographers have attempted to explain the mechanisms by which child deaths tend to cluster in certain families. These explanations have additional significance when seen from a sociological perspective. The clustering of child fatalities is examined in conjunction with biases associated with equality, efficiency, and preference. Parents' efforts to raise both children equally may result in health problems since both sexes need different amounts of nutrient-rich diets. On the other hand, efficiency bias arises when parents spend more on one child than on the others because they think the child will succeed more than the rest. There is a preference bias when parents favor one of their children over the others.[48,49] A child"s health deteriorates as a result of these biases, and as a result, some women may experience frequent child loss.

Socioeconomic development plays a significant role in explaining the clustering of infant fatalities. Along with socio–economic advancement, the provision of basic maternal and child healthcare facilities, including postpartum family planning, can help prevent child deaths. Short birth interval is one of the major factors contributing to the clustering of child deaths. Thus, postpartum contraceptive initiation plays an important role in reducing both maternal and infant mortality.[50,51] In the present technological era, women can be tracked from conception until delivered child becomes two years of age, enabling frontline staff to create an environment that supports women in preventing the loss of a child.

The role of antenatal care is critical since pregnancy outcomes differ for women with and without prenatal care.[52] Among Indian women, antenatal and postnatal care decisions are influenced by their socio-economic, cultural, and individual characteristics[53,54] and by the availability and accessibility of the health services.[55] It has been shown that the utiliztion of antenatal care services may result in the utilization of other maternal health-related services such as institutional delivery and advice regarding post-delivery complications.[56] The clustering of child deaths can be greatly reduced by intervening with proper antenatal care coverage, as it influences the use of healthcare by women later on.

5 | CONCLUSION

This study provides insights into child deaths clustering suffered by mothers in LMICs. Several LMICs, including India, have reported that the death clustering of older siblings affects the younger ones. In light of the high number of child deaths in these countries, it is imperative to pay particular attention to mothers who have experienced multiple child deaths. It would be impossible to achieve the sustainable development goals if mothers in countries experiencing high levels of under-five mortality are not provided with better health and nutrition facilities. It is likely that a few LMICs with high mortality rates and a large population base will have a

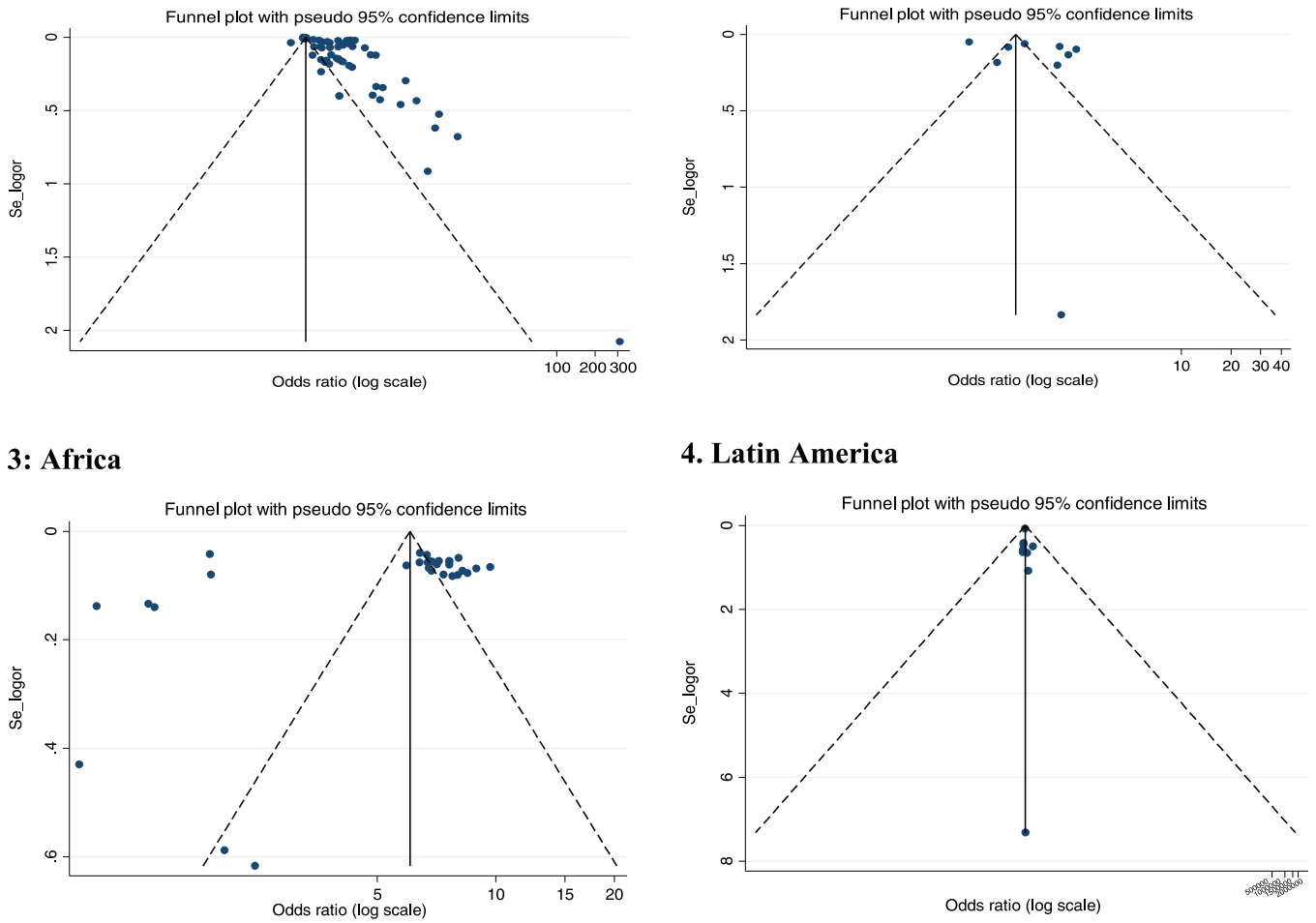

FIGURE 4 Funnel plots for India and other developing regions of world.

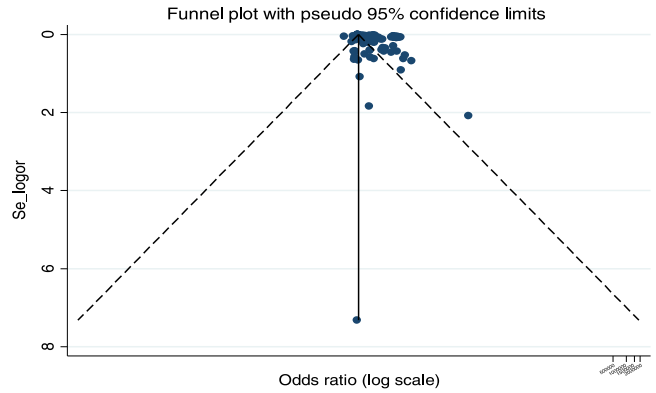

FIGURE 5 Funnel plot for developing regions of world.

significant impact on the global health estimates. Therefore, reducing the burden of childhood mortality in these countries requires a focus on families with clustered deaths. Mothers who have lost multiple children should be targeted for assistance. Most lives, even if not all, can be saved.

AUTHOR CONTRIBUTIONS

Laxmi Kant Dwivedi: Conceptualization; data curation; formal analysis; supervision; validation; visualization; writing—original draft; writing—review & editing. **Mukesh Ranjan**: Conceptualization; data curation; formal analysis; validation; visualization; writing—original draft; writing—review & editing. **Rahul Mishra**: Writing—review & editing. **Waquar Ahmed**: Writing—review & editing. **Mrigesh Bhatia**: Conceptualization; funding acquisition; visualization; writing—review & editing.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

This study is based on published research papers and are available in public domain.

ETHICS STATEMENT

This study is based on published research papers that are available in the public domain. Therefore, no ethical approval was required from any institutional review board.

TRANSPARENCY STATEMENT

The lead author (Dr. Laxmi Kant Dwivedi) affirms that this manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

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