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Original Article

Maternal and child health data quality and the associated factors at public health facilities of Sidama region, Ethiopia: Facility-based cross-sectional study

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Abstract

Background: Data quality is a multi-dimensional term that includes accuracy, precision, completeness, timeliness, integrity, and confidentiality. Efforts have been made to improve maternal and child health (MCH) data quality to enhance decision-making processes regarding maternal and child morbidity and mortality. Despite these efforts, Ethiopia, including the Sidama regional state, still faces significant challenges in reducing MCH morbidity and mortality, which is often exacerbated by suboptimal data quality and utilization. However, the level of data quality remains significantly low, and there is a paucity of information on maternal and child data quality in Sidama regional state, Ethiopia. Therefore, this study aims to assess maternal and child health data quality and factors contributing to data quality in public health facilities of the study area.

Method: A facility-based cross-sectional study was conducted from February 06 to May 05, 2023. A total of 500 health professionals from 23 health centers,3 Hospitals, and 23 health posts were selected using a simple random sampling procedure. Data was gathered using a standardized checklist and self-administered questionnaires. The three common dimensions of data quality, accuracy, completeness, and timeliness, were used to determine the data quality level. Epidata V4.4.1 was used to enter the data, and SPSS Version 25 was used for analysis. To determine the relationship between the variables, bivariate and multivariate logistic regressions were used. The association was reported using the adjusted odds ratio with the corresponding 95% confidence interval, and the significance level was set at a p-value less than 0.05.

Results: The quality of maternal and child health data in the region for accuracy, completeness, and timeliness was 73.00%, 88.80%, and 86.80% respectively. Overall, 79.4% (95%CI; 75.8% - 83.0%) of public health facilities in the Sidama region had Maternal and Child health data quality. Factors significantly associated with good MCH data quality include; a higher level of motivation (AOR = 2.04; 95% CI: 1.25-3.32), high level of self-efficacy/confidence (AOR = 3.43; 95% CI: 1.97-5.97), received written feedback (AOR = 1.81; 95%CI: 1.05-3.10) and having ability of conducting monthly LOT quality assurance sampling (AOR=2.47; 95% CI: 1.32-4.63).

Conclusion: According to the current study, the quality of maternal and child health data in the Sidama region was 79.4% and still requires targeted interventions. The findings highlight that improving data quality is strongly associated with enhancing staff motivation, improving self-efficacy, providing regular written feedback, and ensuring the ability to conduct monthly LOT Quality Assurance Sampling (LQAS). Therefore, strategic efforts focusing on these identified factors are crucial to strengthen MCH data quality, thereby enhancing evidence-based decision-making for reducing maternal and child morbidity and mortality in the region.

Keywords: Maternal and child health, data quality, Sidama region, Ethiopia

Introduction

Data quality is a critical, multi-dimensional concept encompassing accuracy, precision, completeness, timeliness, integrity, and confidentiality (1). Quality data represents what its official source intended or defined, is objective, unbiased, and adheres to established standards (2). Data quality is to guarantee that data is accurate, timely, and consistent enough for the organization to make sound decisions (3).

The health information system (HIS) plays a vital role in maternal and child health (MCH), generating and utilizing data for various purposes. This data is essential for problem-solving, assessing intervention effectiveness, and managing, planning, and evaluating programs that aim to improve the lives of women, infants, and children (2,3).

Routine Health Information Systems (RHIS) are designed to produce high-quality data for effectively tracking and managing population health needs. This information empowers decision-makers to allocate resources, plan, and prioritize services that significantly impact society(4). In Ethiopia, RHIS is central to the "One plan, one budget, and one report" policy. (5) Recognizing this, the Health Sector Transformation Plan II (HSTP II) identified an information revolution as one of its five transformation goals. The RHIS for MCH, in particular, has proven invaluable for monitoring and revising policy implementation and resource allocation(6). However, a lack of quality data and poor usage are affecting the health system's performance and the health of society. This is evident by frequent over- and under-stocks of supplies, poor detection and management of outbreaks, scarcity of human resources at different times, lack of data quality assurance, weak feedback mechanisms, and lack of accuracy, timeliness, and completeness of RHIS reporting (6, 7).

Globally, the quality of data generated by routine HIS in low and middle-income countries remains a significant concern(8). For instance, data quality in Nepal falls below national standards (9). Similarly, many African countries report data quality ranging from 34% to 72%(10). In Ethiopia, data quality is below the 80% national expectation (11), and data completeness, accuracy, and timeliness ranged from 33%-78% in different areas (9, 11). Numerous studies have identified various factors associated with HIS data quality. These include a lack of health professionals' motivation, inadequate HIS task competence, non-functional performance monitoring teams, insufficient supervision, limited RHIS training, low work engagement, heavy workloads, weak management support, lack of accountability for false reports, and poor supportive supervision. (7, 12). However, other equally important factors like technical factors including the complexity of RHIS formats and software scarcity have been given little attention, and thus were not well addressed.

In Ethiopia, to improve maternal and child health data quality, different efforts were undertaken. These include information revolution shifts from old methods of information utilization to the practical use of information undertaken (4). Then, the information revolution sets a priority for the generation and utilization of health information. Furthermore, the Ethiopian Ministry of Health (MOH) introduced the Connected Woreda (local administrative name for the district) Strategy (CWS). Even with these efforts, the maternal and child health data quality in Ethiopia remains a challenge (13).

The health system data quality and use, along with its influencing factors, have been widely examined through research both globally and in Ethiopia (10-12). However, most existing studies focus on general data quality indicators of the system, leaving gaps in our understanding specific to maternal and child health data quality at the national level in general, and in the Sidama regional state in particular (7). To address this, the present study aims to evaluate the quality of maternal and child health data and its associated factors in public healthcare facilities in the Sidama Region, Ethiopia.

Methods and materials

Study Area and Period

This study was conducted at public health facilities of Sidama Region from February 06 to May 05, 2023. The Sidama Region is one of the 11 regional states found in Ethiopia, which is

located 275 Km South of Addis Ababa. Sidama is bordered to the south by the Oromia Region (except for a short stretch in the middle where it shares a border with the Gedeo zone, in SNNPR), on the west by the Bilate River, which separates it from the Wolaita zone. The Sidama region is divided into thirty rural Woredas, six town administrations, and one city administration, and the estimated total population size was 4,873,216 as projected by the 2017 Sidama Regional Health Bureau. The Region has one tertiary hospital, 4 general hospitals, 16 primary hospitals, 138 health centers, 551 health posts, and 173 private facilities (14).

Study design and period

A Facility-based cross-sectional study design was employed

Study subject

The source population comprised all health professionals involved in MCH data quality activities at public health facilities and the facilities in the Sidama Region. The study population consisted of 500 randomly selected healthcare workers enrolled in these activities across selected health facilities and the selected facilities.

Inclusion criteria: this encompassed all public-owned functional health facilities implementing HIS for MCH data activities, and health professionals and health extension workers with more than six months of work experience in MCH data.

Exclusion criteria: New health facilities not yet implementing HIS for MCH data, and health professionals with less than six months of experience were excluded.

Sample Size Determination

The sample size for the first objective

The sample size for the first objective was calculated by using a single population proportion formula based on the following

Table 1: The Sample size calculation for the associated factors of MCH data quality

Variables	CI	Power	AOR	Non-response rate	sample size	Reference
Filling registrations	95%	80%	2.7	10%	262	(14)
Department heads seek feedback	95%	80%	2.48	10%	304	(15)
Provisions of feedback	95%	80%	3.08	10%	296	(8)

assumption; the proportion of the data quality of MCH among public health facilities of Silte Zone (P) = 73% (7), 95% confidence interval (Z), the margin of error (d) was 5% and 10% for non-response rate and 1.5 design effect.

Therefore; total sample size is: n=1.962x0.73 (0.27)/0.052, n=303. By adding10% non-response rate and a design effect of 1.5, the final sample size was 500.

The sample size for the second objective

The sample size calculation for the associated factors was based on significant factors such as filling registrations, department heads seeking feedback, and provisions of feedback in different Studies using open-Epi version 7.2.1 in the table below (Table 1).

As clearly shown in the above calculation and Table 1, the final sample size of 500 was used for this study because it is the largest sample size estimated and is sufficient to address the objectives targeted.

Sampling procedures

Following WHO recommendations (16), 8 Woredas (7 rural and 1 town administration) were randomly selected (20% of the 37 Woredas in the region). Within these Woredas, 3 Hospitals, 23 Health Centers, and 74 Health Posts were proportionally selected. The calculated sample size of 500 healthcare professionals was then proportionally allocated to each selected health facility. Finally, individual healthcare professionals involved in MCH data within these facilities were randomly selected using a lottery method.

Study variables

Dependent variables: MCH Data quality (Good or Poor)

Independent variables:

Socio-demographic factors: age, sex, level of education, position in the case team, work experience

Technical factors: user-friendly, complexity of HIS for MCH formats, software scarcity, trained personnel for entry of data, use of both manual paper and computer-based files, lack of skill in data collection, analysis, information, presentation, and use.

Behavioral factors: knowledge of the content of HIS for MCH form, confidence to use the generated information, problem-solving skills for HIS for MCH tasks, motivation, knowing duties, role, and responsibility.

Organizational factors: get management support for HIS for MCH, get training, get supervision, and get regular feedback.

Data collection methods

Data were collected using structured checklists and questionnaires adapted from the PRISM assessment tools version 3.1 (3, 4). The tool includes a checklist to assess the accuracy, completeness, and timeliness of the data quality. From MCH departments reporting every month, real-time data for 3 months (October, November, and December 2022) was selected to assess data quality with the 2015 EFY (Ethiopian Fiscal Year) data. Based on the national HMIS information use and data quality manual, eight data elements were selected randomly from each selected facility following the top priority indicators identified at the national level (4). These are: antenatal care fourth visit, institutional deliveries, Pentavalent third doses, PMTCT coverage, PNC coverage within seven days, Pregnant women tested for syphilis, measles vaccinated first dose, and Contraceptive accepters rate.

Furthermore, data were collected from individual respondents using a self-administered structured questionnaire that contained background information on the respondent and their responses towards organizational, behavioral, and technical determinants of data quality in the respective health facilities.

Data quality assurance

To ensure data quality, a pre-test was performed on 5% of the sample size outside study areas before actual data collection to check for consistency and to identify any ambiguity on the questionnaire. Based on the pre-test, some of the deviations identified were corrected. The questionnaires from Standard Tools were then translated into Amharic and the local language of Sidamu Afoo.

One day of training was given to data collectors and supervisors on the data collection procedure, the objective of the study, data collection tools, and the significance of the study. During the data collection period, supervision of data collection procedures was conducted by the principal investigator, and onsite technical assistance was given to data collectors. Appropriate correction was given by the principal evaluator at any time during data collection.

Data Management and Analysis

Data was cleaned, coded, and entered into Epi Data version 4.4.1 and was analyzed using SPSS version 25. Descriptive statistics such as mean and standard deviation were calculated for continuous variables, and frequency or percentage was used to describe the categorical variables. Responses of individuals for the determinants assessment were categorized into strongly disagree, disagree, neutral, agree, and strongly agree. During analysis, this category was regrouped and recoded into two categories, ‘strongly disagree’ and ‘disagree’ as disagree, and ‘agree’ and ‘strongly agree’ as agree. Neutral responses are grouped with disagree when the interest is on agree, and vice versa. However, the motivation of the respondents' scores was considered to have a low level of motivation.

Individual responses related to technical and organizational factors related factors were categorized as (0 = No and 1= Yes). However, the knowledge of the respondents was assessed through seven different questions with two response options (0 = No and 1= Yes). After calculating the mean score for each individual, individuals above or equal to the mean score were considered to have a good level of knowledge, whereas a score below the mean score was considered to have a poor level of knowledge. Similarly, the level of self-efficacy or confidence of the respondents was assessed through seven different questions with two response options (0 = No and 1= Yes). After calculating the mean score for each individual, individuals above or equal to the mean score were considered to have a high level of self-efficacy, whereas those scoring below the mean score were considered to have a low level of self-efficacy.

The outcome variable was coded to ‘1’ when the MCH data quality was ‘good’ and ‘0’ when the data quality was ‘poor’. Moreover, the "Good" or "Poor" data quality status of a facility’s MCH reports was then assigned to every one of the 500 individual healthcare professionals who were sampled from that specific facility and were involved in MCH data management. This meant that if a facility’s data was poor, all sampled individuals from that facility were considered to be associated with "Poor" data quality. This approach recognized that individual performance was often reflected in and influenced by the collective output and environment of their

workplace. A binary logistic regression was used to identify factors associated with data quality. Variables with a p-value ≤ 0.25 were candidates for final multivariable regression analysis. The Hosmer and Lemeshow goodness-of-fit test was used to assess model fitness, and a p-value > 0.05 was considered a good fit model.
Crude and adjusted odds ratios with their corresponding 95% confidence intervals were calculated, and variables having a p-value < 0.05 in the multivariable logistic regression were considered to declare significance.

Operational definitions

Data quality is an assessment of data fitness to the degree of data accuracy, completeness, consistency, and timeliness that helps data intended to be used for decision-making to improve service delivery.
Good quality data: the data that fits the criteria for the four quality dimensions of accuracy≥80%, completeness ≥85%, and timeliness ≥85 %(5, 8). The overall quality of the MCH data recorded and reported by the individual sample will be judged as good when all four Quality dimensions' Average value is≥90% level.
Poor quality data: the data that do not fit the criteria for the four quality dimensions (accuracy <80 %, completeness<85%, and timeliness <85%. The overall quality of the MCH data recorded and reported by the individual sample will be judged as poor when all four Quality dimensions' Average value<90% level.
Data Accuracy: was measured by recounting already reported data elements/indicators from the source document or register and compared with the reported to the next level in the reporting format. 3 months' documents were reviewed to see the consistency of selected data elements by selecting the months of October, November, and December. Based on a 10% tolerance for data accuracy will be classified as follows: Over-reporting (<0.90 or 90%), Acceptable limit (0.90-1.10 or 90%-110%), and under-reporting (>or110%). The health facility MCH data is considered accurate if the accuracy score is≥ 90%(6).
Accuracy =the sum of accurate data elements (recounted over reported between $0.9 - 1.1$) / total number of data elements checked$*$100
Completeness: is the average of the source document or registration content completeness and report content. The MCH data is complete if the completeness score is≥ 90%(6).Completeness = % of register content completeness + % of report completeness + % of completeness of report items divided by three.
Register content completeness was measured by the number of completely recorded cases (taking the last 8 elements from the registration of the department for the selected months and dividing by the total cases checked.

Report indicators completeness: Number of data items that are supposed to be filled in by this facility but left blank without indicating "0" in the selected month's report/ Number of expected data items the health center is to report on in the RHIS monthly report. This number does not include data items for services not provided by this health center*100

Timeliness: was assessed as a report submission within the accepted period by observing the reporting date on the reporting form of selected months. The MCH data of the health facility is timely if the average is ≥ 90%(8). Departments at the health posts were expected to report from 20 to the 22nd, and departments at the health centers and hospitals report to the next level from 20 to the 26th.

Results

Socio-demographic characteristics

A total of 500 study participants were enrolled from 49 public health facilities in Sidama regional state, achieving a 100% response rate. The mean age of respondents was 27 ± 2.7 years. The majority of participants were aged 22-27 years, followed by 154 (30.8%) in the 28-33 years age group. Regarding education, approximately 90% of respondents held a level four diploma, while 9.4% were degree holders. Most participants (nearly 85%) were service providers, with 9.8% serving as MCH department coordinators. A significant proportion of respondents (62.4%) had 4-6 years of working experience in RHIS/CHIS data (Table 2).

Table 2: Socio-demographic characteristics of respondents at public health facilities in Sidama region, Ethiopia, 2023

Variables	Category	Frequency	Percentage
Workplace	Hospital	46	9.2
	Health Center	336	67.2
	Health Post	118	23.6
Age	22-27 years	335	67
	28-33 years	154	30.8
	>34 years	11	2.2
Sex	Male	165	33
	Female	335	67
Educational level	Diploma	451	90.2
	Bachelor Degree	47	9.4
	Masters	2	0.4
Role and responsibility of the respondents	Head of the health center	11	2.2
	Department head	49	9.8
	HMIS focal person	11	2.2
	Hospital CEO	3	0.6
	Service providers	426	85.2
Respondents by Profession	Nurse	255	51
	Midwife	103	20.6
	HIT	11	2.2
	HEW	121	24.2
	Others	10	2.0
Work experience in years	1-3 years	129	25.8
	4-6 years	311	62.2
	>6 years	60	12.0
Working experience with RHIS/CHIS data (in years)	1-3 years	139	27.8
	4-6 years	312	62.4
	>6 years	49	9.8

Organizational-related factors

Around eighty percent of the participants have contacted HMIS focal persons seeking help related to HMIS data-related issues. The majority, 383(76.6%) of them know the presence of established PMT in the facilities. Regarding HMIS training, 84.4% of the participants had ever received HMIS/RHIS training, while nearly one-third had taken training in the last three months. Nearly three-fourths of participants had taken supportive supervision from a higher body, and around forty percent had regularly received written feedback from immediate supervisors (Table 3).

Behavioral and Technical Related Factors

The majority (86.6%) of the participants believe that HMIS formats are user-friendly or easily understandable. About 484 (96.8%) and 453 (90.6%) responders had participated in filling the

Table 3: Organizational-related factors of respondents at public health facilities in Sidama region, Ethiopia, 2023

Variables	Category	Frequency	Percentage
Contacted the HMIS focal person for help	Yes	412	82.4
	No	88	17.6
Knowing the establishment of PMT	Yes	383	76.6
	No	117	23.4
Ever received HMIS/RHIS training	Yes	422	84.4
	No	78	15
Training in the last three months	Yes	146	34.6
	No	276	65.4
Types of training provided	Health statistics	10	6.8
	HMIS/CHIS	135	92.5
	Data Analysis and Use	1	0.7
Supportive supervision in the last 3months	Yes	389	77.8
	No	111	22.2
Frequency of supportive supervision in the department in the last 3 months	One time	79	15.8
	Two time	313	62.6
	Three-time	41	8.2
Regularly received written feedback from immediate supervisors.	Yes	199	39.8
	No	301	60.2
Availability of a standard set of indicators with their definition	Yes	254	50.8
	No	246	49.2
Knowing the Presence of an updated HMIS manual	Yes	297	59.4
	No	203	40.6

register or tallying daily and HMIS data aggregation/compilation, respectively (Table 4).
Regarding the ability of participants to conduct LQAS, around 445 (89%) had reported the ability to conduct LQAS to check for data quality. Regarding knowledge related to HMIS data handling, more than two-thirds of the participants have a good understanding of HMIS data handling. Around 237 (47.4%) of participants had a high level of self-efficacy/confidence in executing HMIS data-related tasks to maintain good data quality, whereas 244 (48.8%) respondents had high motivation to be involved in data quality handling techniques (Table 4).

Facility-Based MCH Data Quality

Overall, the magnitude of good MCH data quality at public health facilities in the Sidama region was 79.4% (95%CI: 75.8% - 83.0%), and accordingly the level of MCH data quality in Hospitals, health centers, and health posts was 93.5%, 81.5% and 67.8 respectively (Figure 1).

Dimension of data quality

Data Timeliness

The level of data timeliness in the MCH department was 86.8 % in the health facilities of the study areas. The timeliness of data in the different levels of health facilities, such as hospitals, health centers, and hospitals, was 100%, 89.9%, and 72.9% respectively (Figure 2).

Data Completeness

The data completeness level in the MCH department was 88.8% in the public health facilities of the Sidama region. The completeness

Table 4: Behavioral and technical, and related factors of respondents at public health facilities in Sidama region, Ethiopia, 2023

Variables	Category	Frequency	Percentage
Formats are user-friendly/easily understandable.	Yes	433	86.6
	No	67	13.4
Fill the register or tally daily	Yes	484	96.8
	No	16	3.2
Participated in the aggregation or compilation of data	Yes	453	90.6
	No	47	9.4
Ability to Conduct LQAS	Yes	445	89
	No	55	11
Knowledge of HMIS	Good knowledge	353	70.6
	Poor knowledge	147	29.4
Self-efficacy/level of confidence	High level of self-efficacy	237	47.4
	Low level of self-efficacy	263	52.6
Level of motivation	High motivation	244	48.8
	Low motivation	256	51.2

of data in the different levels of health facilities, such as hospitals, health centers, and health posts, was 95.7%, 89.6%, and 83.9% respectively (Figure 2).

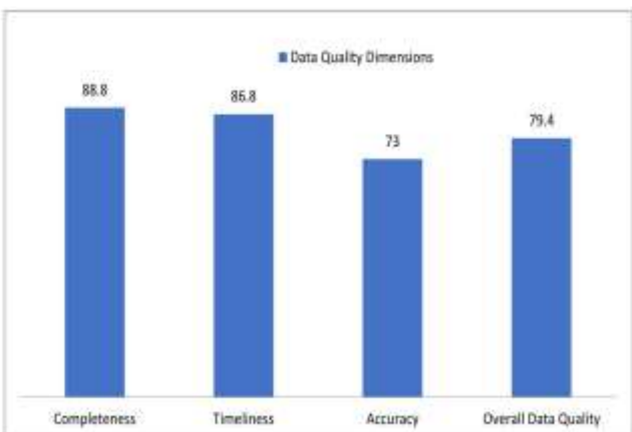

Figure 1: Level of MCH Data Quality at public health facilities in Sidama region, Ethiopia, 2023

Data accuracy

The data accuracy level in MCH departments was 73.0% in the public health facilities of the study areas. The level of data accuracy showed differences among different health facilities, including hospitals, health centers, and health posts where the level of data accuracy was 93.5%, 75%, and 59.3% respectively (Figure 2).

Factors affecting data quality

Initially in the bivariable analysis, the motivation of the respondents, level of knowledge related to data quality, level of self-efficacy or confidence, presence of PMT, reporting format user friendly, fill register or tally daily, regular supportive supervision, given regular written feedback, and conduct monthly LQAS were selected as candidate variable for multivariable logistic regression analysis by fulfilling the predetermined cutoff point ($p < 0.25$).

After controlling for possible confounders in multivariable logistic regression, four variables (level of self-efficacy or confidence, conducting monthly LQAS, motivation of the respondents, and giving regular written feedback) were found to be independent factors of data quality.

Accordingly, the likelihood of reporting quality maternal and child health data among respondents with high levels of motivation was 2 times higher compared to their counterparts (AOR = 2.04, 95% CI = 1.25-3.32). The odds of reporting quality maternal and child health data among respondents with a high level of self-efficacy were 3.4 times higher than those with a low level of self-efficacy (AOR = 3.43, 95% CI = 1.97-5.97).

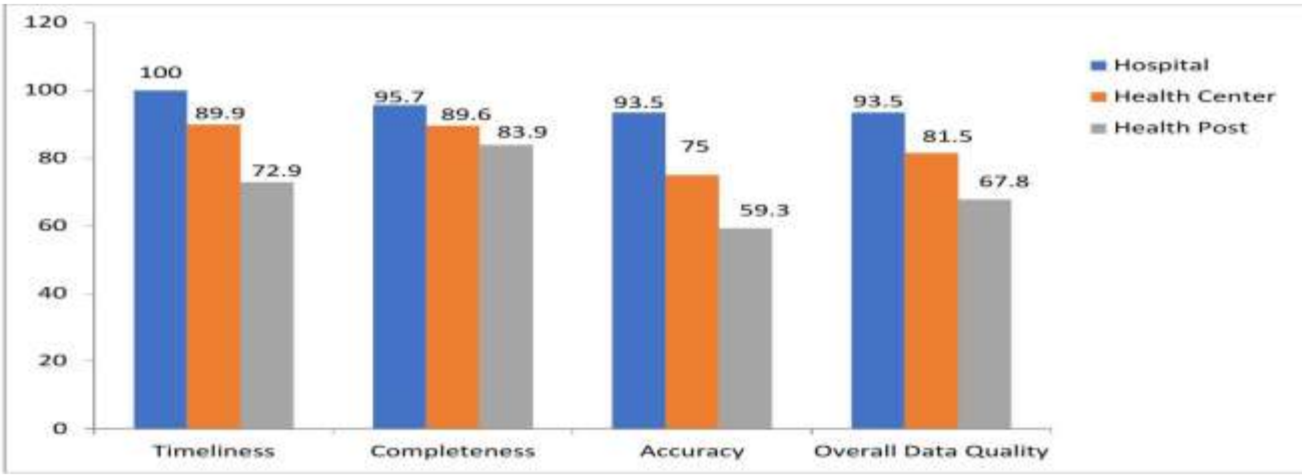

Figure 2: Level of data timeliness, completeness, accuracy, and overall data quality by type of health facilities in Sidama region, Ethiopia, 2023

Respondents who received feedback were 1.8 times more likely to report quality maternal and child health data as compared to the departments that did not (AOR = 1.81; 95% CI = 1.05-3.10). Respondents who conduct monthly LQAS were 2.5 times more likely to report quality maternal and child health data compared to their counterparts (AOR=2.47,95% CI = 1.32-4.63) (Table 5).

Table 5 Multivariable logistic regression analysis of factors associated with data at MCH departments of public health facilities in Sidama region, Ethiopia, 2023

Variables	**Category**	**Data quality**		**COR (95% CI)**	**AOR (95% CI)**
		Good	**Poor**		
Motivation level	High	209	35	2.16 (1.37, 3.40)	2.04 (1.25, 3.32) **
	Low	188	68	1	
Level of knowledge	Good	293	60	2.02 (1.29, 3.17)	1.14 (0.68, 1.92)
	Poor	104	43	1	1
Level of self-efficacy or confidence	High	215	22	4.35 (2.61, 7.25)	3.43 (1.97, 5.97) **
	Low	182	81	1	
Presence of PMT	Yes	312	71	1.65 (1.02, 2.68)	1.06 (0.61, 1.84)
	No	85	32	1	1
Reporting format user-friendly	Yes	349	84	1.65 (0.92, 2.94)	1.38 (0.73, 2.62)
	No	48	19	1	1
Regular supportive supervision	Yes	321	68	2.17 (1.35, 3.51)	1.47 (0.86, 2.51)
	No	76	35	1	1
Given regular written feedback	Yes	174	25	2.43 (1.49, 3.98)	1.81 (1.05, 3.10) *
	No	223	78	1	1
Conduct monthly LQAS	Yes	367	78	3.92 (2.19, 7.03)	2.47 (1.32, 4.63)
	No	30	25	1	1

***Significant at a p-value <0.05 level and ** at a p-value <0.001**

Discussion

The quality of maternal and child health data in the region, based on accuracy, completeness, and timeliness, was 73.00%, 88.80%, and 86.80%, respectively. Overall, good MCH data quality coverage of the region was scored, which was below the national target. The overall data quality of the selected public health facilities of Sidama region scored 79.4% (95%CI = 75.8% - 83.0%), which is in line with a previous study conducted in Addis Ababa, 76.22% (6), and Hadiya zone, 83% (15).

However, this result is below the target set by the FMOH, which is at 90%. Contrary to this, findings reported in Benin, 45% (16)), west Gojjam zone, 74% (18), Dire Dawa, eastern Ethiopia, 75.3% (11), Harari region, 51.35% (19), and Southern Ethiopia, 82.5%(17), indicated lower magnitude of data quality. These variations might be attributed to differences in study settings, health service coverage, and organizational culture regarding data quality. This overall finding underscores the persistent gap in meeting national data quality standards, suggesting a need for continued efforts to strengthen health information systems in Sidama.

The accuracy of MCH data at public health facilities of Sidama region was 73.00% (69.1%, 76.9%), which is in line with a study conducted in Rwanda, 73.3% (20), West Gojjam zone, 74% (18). However, this study scored higher than a study conducted in Kenya, 56% (19), Harari region, 58.1%(8), east Wollega zone, 48% (20), and scored less than findings done in Nigeria 79% (10), Jigjiga, 88.12% (7), Addis Ababa, 77.67% (6), Hadiya Zone, 79%(14). The observed variation could potentially be attributed to the difference in facility type and the quality of feedback provided to the respective departments, as well as the levels of human resource expertise available.

Concerning completeness of MCH data, the selected public health facilities of Sidama region scored 88.8% (86.0%, 91.6%), which is comparable with a study conducted in India, 88.5% (20), east Wollega zone, 86% (21) and Hadiya zone, 86% (14). But, our findings of completeness of MCH data are higher than the completeness reported elsewhere;75% in Nigeria(10), 44% in Kenya(21), and 70% in the west Gojjam zone (18), whereas, this study scored less magnitude reported in Rwanda, 97.6%, (19) and Addis Ababa, 96% (6).

This study also revealed that from the studied public health facilities of the Sidama region, 86.8% (83.8%, 89.8%) of the MCH department submitted their report on time. This is in line with a study conducted in the Hadiya zone, 84% (14), southern Ethiopia, 88.4% (16). In this study, the timeliness of the MCH data report was high compared to the study in Kenya, 32% (21), west Gojjam zone, 78% (18). However, it is lower than a study done in Rwanda, 93.8% (19), Harari region, and 93.7%(8). The possible justification for the above-mentioned discrepancy in terms of completeness and on-time report of MCH data might be due to a difference in study period, facility type, and place of study.

The other purpose of this study is to identify associated factors of MCH data quality at public health facilities. As a result, the motivation of the respondents, level of self-efficacy or confidence, regular written feedback, and conducting monthly LQAS were independent factors of MCH data quality. According to this study, MCH departments with motivated service providers were two times more likely to have good-quality MCH data as compared to departments that did not have motivated service providers. This was similar to evidence from previous studies done in Benin (24), Kenya (25), and Ethiopia (22). The possible explanation might be that motivation may boost the morale of service providers and establish a competitive environment, which in turn increases the data quality of the department. This finding implies that fostering a positive work environment and recognizing staff efforts can significantly enhance data quality.

Interventions aimed at boosting staff morale and promoting a competitive yet supportive atmosphere are likely to be effective.

Multivariable analysis results also indicated that departments that have service providers with high levels of self-efficacy or confidence increase the odds of good-quality MCH data by more than three times compared to departments that have service providers with low levels of self-efficacy or confidence. This evidence is in agreement with previous studies conducted in Benin(17), South and southern Ethiopia (14). This may be because having enough confidence to perform data management activities may encourage service providers to come up with better innovations to improve data quality.

In this study, departments that received regular written feedback were nearly two times more likely to have good-quality data as compared to their counterparts. A similar finding was found in studies done in Dire Dawa (11) and the Harari region (8). The reason behind this finding is due to the fact that feedback is key in addressing quality issues by helping to improve the overall performance of data management for better achievement of data quality. This highlights the importance of robust supervisory mechanisms and communication channels. Regular, constructive feedback acts as a critical tool for identifying and addressing data quality issues, leading to improved overall performance in data management.

Finally, conducting monthly LQAS was another factor that increased the likelihood of good-quality MCH data by more than two times compared to departments that do not conduct monthly LQAS. These findings support those of Getachew et al. in the Hadiya zone (14), which highlighted a positive relationship between checking data quality monthly and data quality. A possible justification might be that conducting data quality checks regularly helps to identify gaps and make corrections accordingly so as to improve data quality. This strongly implies that routine data validation and quality assurance mechanisms, such as LQAS, are essential for identifying gaps proactively and enabling timely corrective actions, thereby systematically improving data quality.

Limitations of the Study

This study has several limitations. First, its cross-sectional design prevents establishing cause-and-effect relationships. Second, the reliance on self-reported data introduces potential social desirability bias. Third, the findings may not be fully generalizable beyond the Sidama region due to regional variations and the exclusion of private facilities.

Conclusion and Recommendations

This study emphasizes the critical need for continued efforts to improve maternal and child health data quality in public health facilities within the Sidama region, Ethiopia. Despite the reported overall good data quality, persistent challenges were identified across key dimensions like timeliness, completeness, and accuracy, particularly varying across different facility types. Our findings highlight that high motivation, strong self-efficacy, regular feedback, and consistent use of data quality assurance mechanisms like monthly Lot Quality Assurance Sampling (LQAS) are crucial factors driving improved data quality.

Recommendations:

Based on the findings of this study, we recommend the following actions to enhance maternal and child health (MCH) data quality in public health facilities in the Sidama region:

- Implement strategies to enhance the motivation and self-efficacy of health professionals managing MCH data.
- Establish clear protocols for providing regular and constructive written feedback on MCH data quality.
- Prioritize training and support for consistent monthly Lot Quality Assurance Sampling (LQAS) to improve data quality checks.

• Offer focused capacity-building training to address specific data quality gaps.
• Undertake qualitative studies to explore health workers' perceptions and systemic challenges in MCH data management.

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Ethical considerations

Ethical clearance was obtained from the institutional review board (IRB) of Hawassa University College of Medicine and Health Science. A formal letter was written to the Sidama Region Health Bureau by Hawassa University College of Medicine and Health Science, School of Public Health. The data collection was conducted after permission was obtained from health facilities. Privacy and confidentiality were respected by not using personal identifiers like names, addresses, or any other private information. The data was held anonymously and confidentially throughout research activities.

Data availability statement

We described all the relevant information in the manuscript, but the refined dataset can be obtained from the corresponding author upon reasonable request.

Conflicts of interest

The authors declare that there is no conflict of interest.

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