A mixed-methods assessment of Routine Health Information System (RHIS) Data Quality and Factors Affecting it, Addis Ababa City Administration, Ethiopia, 2020

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Abstract

Background: Effective and efficient health care services need evidence-based decisions, and these decisions should rely on information from high-quality data. However, despite a lot of efforts, routine health data is still claimed to be not at the required level of quality. Previous studies have primarily focused on organization-related factors while little emphasis was given for perception and knowledge of service providers' gaps. Therefore, this study aims to evaluate the quality of data generated from routine health information systems and factors contributing to data quality from diverse aspects.

Objective: This study aims in assessing the quality of routine health information system data generated from health facilities in Addis Ababa city administration, providing the level of data quality of routine health information system, and factors affecting it.

Method: A cross-sectional study was conducted on 568 health professionals from 33 health centers selected randomly using a two-stage sampling method. A qualitative study was also conducted using 12 key informants.

Result: The overall regional data quality level was 76.22%. Health professionals' motivation towards routine health care data have shown a strong association with data quality, (r (31) =.71, p<.001). Lack of adequate Health information system task competence, non-functional PMT, and lack of supervision was also commonly reported reasons for poor data quality.

Conclusion: This review has documented the data quality of routine health information systems from health centers under Addis Ababa city. Overall data quality (76.22%) was found to be below the national expectation level, which is 90%. The study emphasized the role of behavioral factors in improving the quality of routine health care data.
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Keywords: RHIS, Accuracy, completeness, timeliness, consistency, Addis Ababa

Background

A Routine Health Information System(RHIS) is a system designed for regular collection, processing, use, and dissemination of health-related data to improve the management of programs, resources, and health care outcomes (1).

RHIS has been practiced for over a century globally. However, it was restricted to developed countries. Developing countries start to emphasize RHIS recently(2). Ethiopia has also started to implement The Health Management Information System (HMIS) in 2008 which is designed to generate routine data use for decision making at different levels of the health system(3). It starts with 108 indicators for monitoring the performance of various health services and the availability of health resources. However, due to the gap in monitoring the Health Sector Development Plan (HSDP), the emergence of new initiatives such as new vaccines (MCV2, HPV1, HPV2and IPV) and community based neonatal care and nutrition service, and the focus on new priorities such as emerging diseases and expansion of control programs like NCD, those indicators have been revised in 2014 to be 122 and again revised to a total of 131 indicators in 2017 through discussions and consultations with stakeholders(4,5).

The growing need for information by quantity and quality in the health sector drives the information revolution to be one of the four transformation agendas in HSTP. The main objective of this reform is to enhance the use of accurate and reliable information for decision making at the local level through a radical shift from the traditional way of data utilization to systemic information management by promoting the culture of information (6).

Effective and efficient health service policy needs a reliable routine health information system that can generate quality health care data for assessing whether the desired result has been achieved after an action is taken to solve a problem(7). However, in developing countries data from RHIS are often untimely, incomplete, inaccurate, and inconsistent (8–13).

The National Health Data Quality Review, conducted in 2018 using the World Health Organization's data quality review tool, results show that in Ethiopia, health facilities' Data quality remains low throughout the country(14).

Improved data quality leads to better decision-making across an organization. So, excellence in data quality enables health care organizations to plan and provide effective and efficient service for users and to meet their target(15).

Routine health information system data quality is affected by several factors, PRISM framework groups factors that contribute to data quality into three categories(16).

Technical determinants

Technical determinants are factors that are related to technology to develop, manage, and improve RHIS processes and performance. Those factors are referred to as the development of indicators, designing data collection forms, and preparing procedural manuals, processes, systems, and methods(16). The effect of

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technical factors on RHIS is supported by an empirical investigation on data warehouse adaptation; the study claims the complexity of IT infrastructures is a key determinant for the adaption of new information systems(17). Besides having the right user attitude and skills with good leadership, designing a user-friendly health information system is inevitable for data quality improvement (18).

Organizational determinants
These factors can be the type and size of facility, culture, politics, hierarchy, planning and control system, strategy, management, and communication. The PRISM framework considers organizational determinants key for affecting performance. It defines this category as all those factors that are related to organizational structure, resources, procedures, support services, and culture to develop, manage, and improve RHIS processes and performance(16,18). In addition to organizational structures, such as the availability of sufficient room for HMIS activity, external factors like inadequate supporting infrastructures, like electric power supply, poor road transportation, and telecommunication affect RHIS performance significantly (19–21).

Behavioral determinants
In Addition to technical and organizational factors, individual-level factors affect the practice of RHIS tasks(22–26). If people appreciate the usefulness of RHIS tasks, feel confident and competent in performing the task, and perceive that the task's complexity is challenging but not overwhelming, then they will complete the task persistently(16).

Previous studies done on RHIS performance have limitations to give a clear image of the level of data quality and factors contributing to data quality. Some are program-specific studies that use indicators from only one program area and others are done on a single facility. Therefore, in this study indicators from multiple program areas were incorporated and a total of 33 facilities from all sub-cities of Addis Ababa city administration were included.

The introduction of a web-based reporting platform at the facility level helps in the standardization of data collection which ultimately improves data quality. However, there is a lack of research-based evidence on the current state of data quality in Addis Ababa after the introduction of DHIS2.

Accurate and reliable patient data, such as past medical history, have a substantial role in improving patient health outcomes. Health professionals are more likely to give better and safe care if their decision is based on accurate and reliable data. So, information from the patient folder has a substantial role in the quality of care. However, to the knowledge of the author, previous studies were not considering its role. So, this study aims to incorporate medical records data quality assessment.

Objective
***General objective**:* to assess the quality of routine health service data and factors contributing to data quality collected in health centers of Addis Ababa City Administration in 2020.

Specific objectives
- To Assess the timeliness of routine health data in Addis Ababa City Health Centers in 2020.
- To Assess the completeness of routine health data in Addis Ababa City Health Centers in 2020.
- To Assess the consistency of routine health data in Addis Ababa City Health Centers in 2020.
- To Assess the accuracy of routine health data in Addis Ababa City Health Centers in 2020.
- To identify factors contributing to the data quality of routine health information system in Addis Ababa City Health Centers in 2020.

Method
Study Area
Addis Ababa is the capital city of Ethiopia with a total population of 3,774,000 according to an estimate of the Central Statistical Agency(27). Addis Ababa is one of the two city administrations of the Federal Democratic Republic of Ethiopia. The city has three administrative levels: city administration at the top, ten sub-cities, and 126 woredas. Addis Ababa Health Bureau is responsible for the overall health activity in the city. The city has 99 health centers, 40 private hospitals, and 12 state-run hospitals. The city has also 89 higher,110 medium, 98 lower, and 90 specialized clinics.

The target population for the study is all public health centers in Addis Ababa City administration. All functional health centers during the data collection period were included. Health centers converted to COVID-19 treatment centers were excluded.

Study design and period
The study used a mixed method approach. The mixed study approach is the type of research in which the researcher merges elements of quantitative and qualitative research approaches to expand and strengthen the study's conclusion(28). A facility-based cross-sectional study was conducted to assess the data quality level of health centers and factors affecting it in May 2020. The qualitative study was conducted in June 2020 for the corporation and enhancement of survey results.

Study variables
***Dependent variable*:** Routine health service data quality
Independent variables:
Behavioral determinants
Organizational determinants
Technical determinants

Data collection procedures
Quantitative data was collected using the customized performance of routine health information system management tools. These tools were developed for the evaluation of RHIS performance. OBAT, MAT, and facility checklist tools were used to collect behavioral and organizational determinants of routine health data quality.

A key informant interview was the method used to collect the qualitative data. A semi-structured interview guide was used to interview 12 key informants. Service provider staff in health centers, HMIS focal persons, facility managers, sub-city officials, and regional health bureau officials were interviewed face to face by the researcher.

Sample size and Sampling process

Facility sample size calculation involves kappa statistics as measuring the quality of data depends on the agreement between reported data and recounts from source documents. The agreement is a product of marginal prevalence (i.e., the chance of finding both the source document and monthly report), and the expected proportion of agreement (P1) in the counts for the key service outputs being confirmed from the source document and monthly reports. Here we have two percentages of agreements: minimum acceptable agreement (Po) and expected agreement by the study (P1). Since there was not enough knowledge concerning to availability of source documents and monthly reports, 30% marginal prevalence of finding both documents were considered. Accordingly,

α type1error value=0.05
β power =80%
Po = 75%
P1 = 95%
Marginal prevalence(π) = 30%

Non centrality (λ) is expressed as a function of sample size and test statistics, the value of λ for α of 0.05, β 80% and degree of freedom 1 is 7.849 so,

$$N = \frac{\lambda}{(p1-po)^2\{\frac{Po}{(po+\pi\times 2-1)(po-\pi\times 2+1)}+\frac{1}{(1-Po)}\}}$$

$$N = \frac{7.849}{(0.95-0.75)^2\{\frac{0.75}{(0.75+0.3\times 2-1)(0.75-0.\times 2+1)}+\frac{1}{(1-0.75)}\}}$$

N=33

Using a probability proportional sampling method 33 health centers were selected from a total of 99 health centers from the ten sub-cities.

Sample size determination to assess service provider behavioral factors contributing to data quality was based on single proportion formula taking estimated proportion assuming 60% prevalence observed HMIS task competence in southern Ethiopia(29) and 95% confidence level, 5% margin of error taking design effect 1.5 and 5 % non-response rate

$$n = \frac{(Z_{1-\alpha/2})^2 \times p \times (1-p)}{d^2} * g$$

$$n= \frac{\mathbf{(1.96)^2(0.60(1-0.60))*(1.5)}}{\mathbf{(0.05)^2}} = \mathbf{554}$$

Adding 5% for non-response final sample size were 582 health professionals. Health professionals were selected using a two-stage sampling method. First, a sample of health centers was selected randomly, and then a sample of staff within the facility.

Operational definition

Good quality of data is

1. data accuracy score ranges from 90% to 110% and
2. completeness scores greater than 95% and
3. consistency Modified Z- score below 3.5
4. report summited before the deadline (26^{th} of the $month$)

Health facility data quality was assessed using four dimensions; a weighted average of those dimensions was used to compute a single weighted measure of data quality. Table 1 the weight given for data quality dimensions (30).

Table 1: **Weight given for data quality dimensions, in Addis Ababa city health centers, 2020**

Dimension	**Weight**
Accuracy	0.40
Completeness	0.30
Timeliness	0.20
Consistency	0.10

Completeness

To calculate Completeness three metrics which are completeness of facility report, completeness of indicator data, and source document completeness were assessed.

Timeliness of facility reporting: is measured by whether the facility date of report submission to the highest level is not beyond the deadline. DHIS2 generated health center's timeliness score was used for this metric.

Consistency

Internal consistency of reporting data: Consistency of reported data from 12 program indicators over one year was assessed. The percentage of extreme outlier months within the health facility report for the selected indicators were computed.

Consistency between related indicators: Consistency between the number of children under one year of age who have received the third dose of pentavalent vaccine and the number of children under one year of age who have received the third dose of pneumococcal vaccine was also assessed.

Accuracy

Accuracy of reported data assessed using verification factor. It is calculated by dividing recounted data from the source document for the selected indicators by reported value. Fourteen indicators were selected for assessing data accuracy.

Data cleaning and analysis

Data were entered using Epi-info version 7 and cleaned for missing value and exported to SPSS version 23 for analysis. Descriptive statistics using mean, median, and modified standard deviation estimates were used for measuring dimensions of data quality. Besides, correlation and non-parametric tests were conducted between the data quality score of health centers and data quality indicators. One-way ANOVA was also conducted to assess whether data quality dimensions scores of health centers vary across sub-cities.

The audio files from the interviews were transcribed and then translated into the English language carefully. After a verbatim transcription Codes, codebook, and networks were created using Atlas ti version 7.5 software. Thematic analysis method was used to find similar patterns from the interviews to form themes representing the major streams of thought of the interviewees. The identified themes were later connected to identify factors affecting the quality of data from the routine health information system.

A two-day training was given to three BSc degree nurse graduates and three diploma health informatics technician graduates as data collectors and two MSc degree public health graduates as supervisors. A pretest of the data collection instruments was conducted on 20 health professionals to identify survey items that may need modification.

Ethical clearance was obtained from the institutional research review board of Addis Ababa University, College of Health Science and Addis Ababa public health research and emergency management directorate. Permission was also served by the respective health center management and informed written consent was also gained from each respondent.

Result

A total of 33 health centers in Addis Ababa city were included in the study. A total of 568 respondents from different departments and service areas were involved making the overall response rate to be 97.6%. Regarding service year, 277 (48.8%) of them have less than five years of experience. Related to position in the organization, from the total of respondents, 406(71.5%), 101(17.8%), and 61(10.7%) were medical staff, department heads, and data clerks, respectively.

Data Quality

The overall regional data quality was 76.22%, ranging from 68% at Yeka health center to 92% at Shiromeda health center. Table 2 presents the data quality level of health centers aggregated by their sub-city.

Table 2: **Data quality status of health centers aggregated by sub-city in Addis Ababa, May 2020**

Sub-city	Completeness	Timeliness	Accuracy	Consistency	Data Quality
Addis Ketema	87.22	66.67	78.00	96.27	80.33
Akaki Kality	93.14	22.22	77.00	96.20	72.81
Arada	92.13	66.67	64.67	97.90	76.63
Bole	85.96	55.56	80.33	96.97	78.73
Gulele	93.30	33.33	73.00	96.98	73.55
Kirkos	93.65	77.78	71.00	97.90	81.84
Kolfe Keraniyo	92.36	25.00	92.00	98.23	79.33
Lideta	93.42	16.50	77.50	97.90	72.12
Nifas-silk Lafto	89.18	41.67	74.25	96.18	74.40
Yeka	91.16	13.33	82.20	96.52	72.55
Regional	91.15	41.87	77.00	97.11	76.22

Consistency

From a total of 4752 monthly reports, 148 monthly reports were outliers. Thus, about 3% of reports from health centers in Addis Ababa city were inconsistent. Consistency between related indicators is evaluated by comparing Penta3 and PCV3 reported data. The result looks good no sub-city has a largely discrepant value, (Regional ratio was 100%, Sd =1.37%).

Accuracy

The average report accuracy in Addis Ababa city administration health centers is 77.67%, sd =9.65. Only five (15.5%) health centers' monthly reported data were within the acceptable threshold of accuracy (90%-110%). Median verification factor calculation of program indicators shows that only 8 out of 14 were in an acceptable range of deviation. The number of malaria tests and total contraceptive acceptors was over-reported by 11%. The number of adults and pediatric patients with an undetectable viral load in the reporting period was under-reported by 11%.

Timeliness

The timeliness of the health centers report was assessed using the DHIS2 generated timelines report. The median report timeliness score of the health centers was 33.33%, ranging from 0%-100%.

DHIS2 considers the last date of the data edition for timeliness report and with every data correction of a given monthly report after deadline day, the timeliness score will be reduced by 10%. Due to this, in order not to lower the monthly performance, some HMIS focal prefers to adjust incorrect data elements lately even after quarter reports had been submitted. That is why correlation analysis between the monthly health center's timeliness and accuracy score shows a mild negative correlation, (r (31) =-.36, p=0.038).

Completeness

Report and source document completeness were 93.93% and 96%, respectively. However, monthly reports significantly lack to incorporate indicators for diabetic patients who visited the facility, P-value of (0.012). One-sample Wilcoxon signed-rank test results also showed, median Verification factor for the number of diabetic patients visiting in the reporting month was significantly different from the ideal median value of 1 (see tables 3 and 4).

Table 3: **Completeness of indicator data in Health centers, Addis Ababa, Ethiopia 2020**

	Sub-City	**ANC1**	**Penta1**	**DM patients visited the facility**	**Number of OPD visits**	**received 100% of prescribed drugs**
1	Addis Ketema	100%	100%	38.9%	100%	50%
2	Akaki /Kality	100%	97%	44.4%	100%	86%
3	Arada	100%	100%	41.6%	97%	86%
4	Bole	100%	100%	44.4%	100%	56%
5	Gulele	100%	100%	44.4%	100%	100%
6	Kirkos	100%	100%	42%	100%	100%
7	Kolfe	100%	100%	41.6%	100%	100%
8	Lideta	100%	100%	45.8%	100%	100%
9	Nifas silk	100%	100%	37.5%	96%	64.5%
10	Yeka	100%	100%	36.6%	90%	73.3%
Reginal		100%	99.7%	41.72%	98.30%	81.58%

Table 4: **Median VF of data elements and deviations from the ideal value, Addis Ababa,2020**

Indicator	**Median**	**Minimum**	**Maximum**	**Range**	**P-value**
DM	1.02	0.91	25.35	24.44	.044
HTN	1.03	0.52	30.91	30.39	.114
ANC1	1.01	0.88	1.54	0.66	.060
ANC4	1.00	0.82	1.89	1.07	.696
VL	1.11	0.51	6.33	5.82	.057
Malaria test	0.89	0.04	3	2.96	.513
Penta3	1.00	0.18	2.19	2.01	.398
VCT	1.00	0.17	1.99	1.82	.069
Prescription	1.00	0.41	38.29	37.88	.211
TT1	1.00	0.45	1.41	0.96	.452
New contraceptive acceptors	0.97	0.52	18.69	18.17	.100
Total contraceptive accepters	0.89	0.28	1.95	1.67	.014
New TB case	1.00	0.23	1.17	0.94	.655
TB case on treatment	1.00	0.23	1.17	0.94	.655

When a key informant was asked of the reason for it: “*One factor is those indicators are recent and weren't included in the revised HMIS. Some sub-cities have printed out that section to fill in the added indicators and report using that. So, what we do for the near future is that there's a new form of registry ordered so the facilities are supposed to be using that afterward since we already gave them the softcopy*”

Factors of Data Quality

In this study 49.5% of staff and 98.4% of HMIS focal persons are trained and 74%, 83%, and 72% of respondents perceived that they could perform data quality checks, interpret data, and prepare data visuals, respectively (see figure 1).

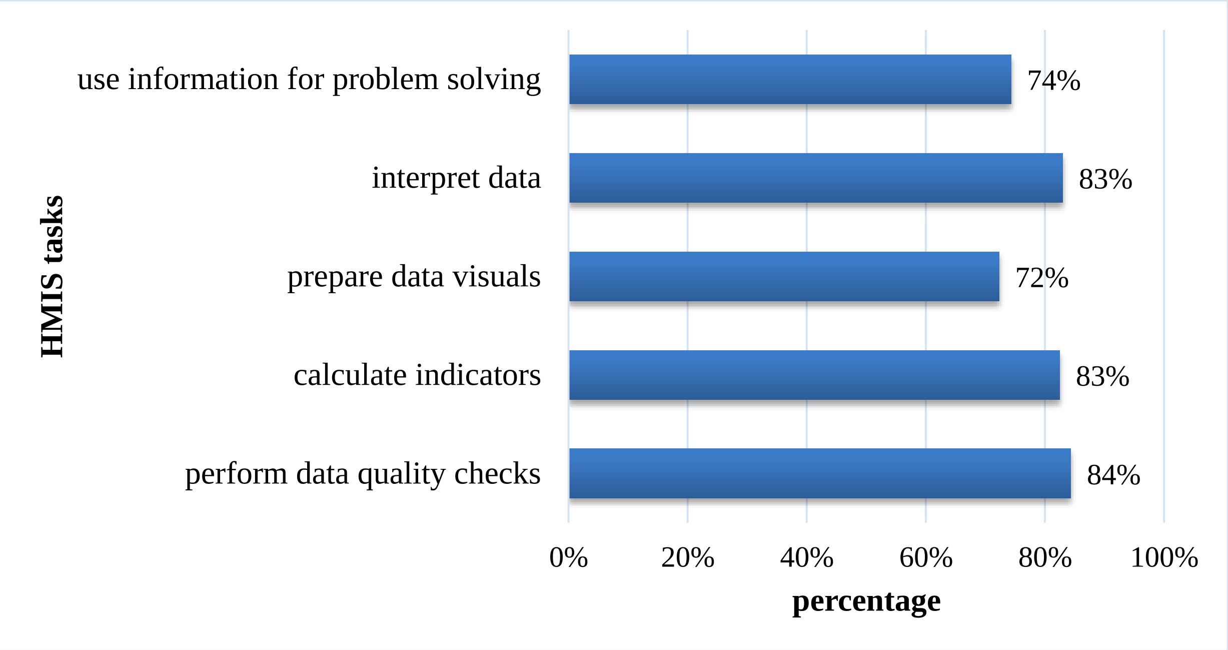

Figure 1: **Perceived Confidence Level for HMIS Tasks staff in Health centers in A.A, Ethiopia 2020**

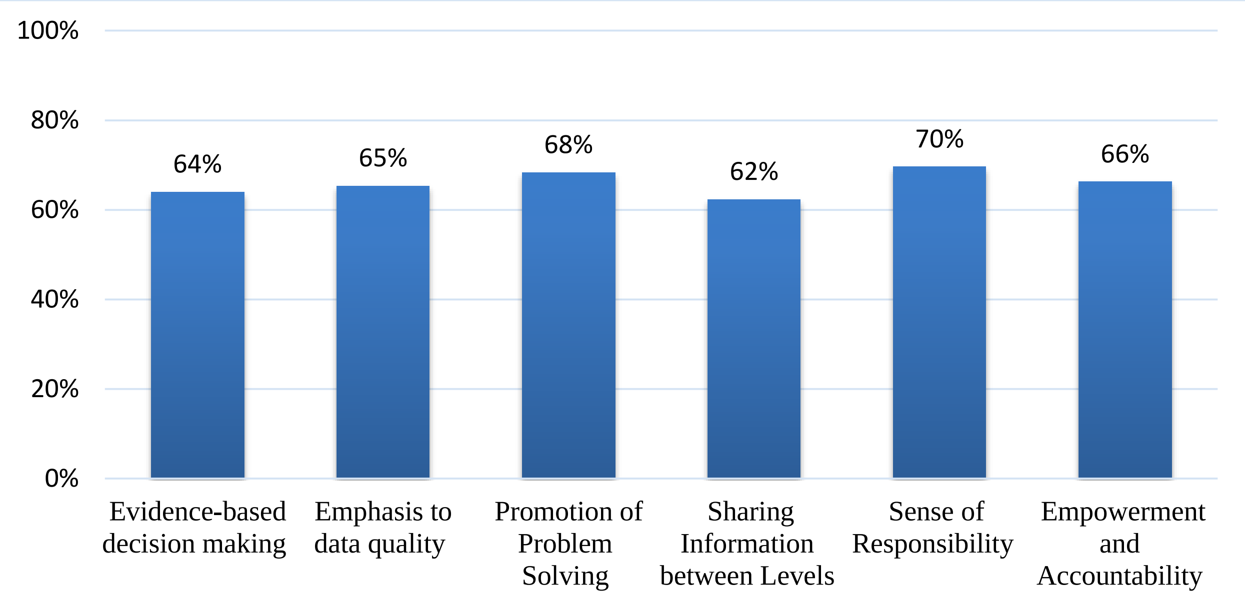

Figure 2: **perceived Culture of information use in Health centers, Addis Ababa Ethiopia 2020**

Results of correlation test indicated that there was a strong positive association between health center data quality level and the percentage of staff who perceive that the organization promotes a culture of evidence-based decision making, (r (31) =.78, p<.001).

Correlation test result also indicated that the motivation of service providers and health center data quality was found to be strongly positively correlated, (r (31) =.71, p<.001). A key informant also mentioned a lower motivation level as a root cause for poor data quality. Some health professionals do not consider recording and reporting as part of their routine activities or they just give more priority to the clinical part and lesser attention to data quality. The quantitative part of this study also strengthens this finding, 58.69% of respondents included in the survey find collecting or recording data to be tedious activity and 52.72% of participants feel that data collection/recording is not the responsibility of healthcare providers.

This behavior is mainly manifested by physicians at health centers but not limited to them. A respondent emphasized this like:

"The staff as well tend to give less attention to reporting and they don't give it as much value as treating patients when there's workload…Some staff members even asked me what am I being paid for and that it's just my job/responsibility"

The Presence of parallel reporting and unstandardized source documents have also their own implications on service provider's perception toward routine health data collection practice. The respondent emphasis this like:

"The problem arises when there are other organizations/partners that have their own need too and this is mainly shown in HIV/AIDS programs. For instance, if you go and see the ART room there are more than 10 registry forms and I know this should be harmonized and integrated into that of the Ministry of

Health and this problem has been there for a long time and hasn't yet been solved".

One Way ANOVA and Kruskal Wallis test results show data quality were significantly different across sub-cities. This could be due to gaps in supervisory visit. From the sampled 33 health centers only 16(48.5%) of them had received a supervisory visit within the last three months. A chi-square test of independence was performed to examine the relationship between health facility data quality and having a supervisory visit and the relation between these variables was significant, X^2 (1, N = 33) = 6.79, p = .009. Facilities that received supervisory visits were more likely to have better data quality than those without.

All sampled health centers had performance monitoring team (PMT) and Logbook assessment shows that from the selected three months for review all health centers had at least two recorded meetings. However, non-functional PMT meeting was mentioned as the main cause of the data quality problems by the administrative unit key informants. The performance monitoring meetings that were designed for the sole purpose of improving data quality are not functional enough to increase data quality. When asked about the functionality of PMT meetings, an administrative level participant said this:

"We have noticed that all of the meetings are written and signed by one person. We have even observed in some facilities people trying to run around to get the signatures of the medical director and the core processor on the PMT agenda notebook when we do sudden visits"

Discussion

The overall data quality of health centers under Addis Ababa city Administration is found to be 76.5% and majority of health centers' reported data were not within the expected threshold level of accuracy (90%-110%). Only 15.5% of facilities reported accurately, which is lower than the study conducted in Nigeria where 54.17% of facilities reported accurately(31). One reason for this difference is the tighten (10%) tolerance of data accuracy in this study compared to 15% of tolerance taken by the later study. In this study, the data quality problems were observed in all indicators. Nevertheless, the data accuracy assessment was not equally poor across program areas. An evaluation of the accuracy of HIS data in the Southern Nations, Nationalities and People's Region (SNNPR), Ethiopia, (32) supports the concern that there is a systematic inaccuracy of reports between indicators. Even if errors were found in nearly all reviewed indicators most facilities over-reported services' indicators while under-reporting that of diseases. Unlike other studies(8,32,33), in this study indicators related to maternal and child health have shown promising results and almost all health center reported accurately for TB related indicators. It might be due to strict follow-up in those program areas. However, in our study data quality of indicators related to diabetes and hypertension is drastically compromised; most health centers missed to incorporate non-communicable disease data elements in their report and these reports were inaccurate.

Report completeness of health centers in this study is 96%. Similarly, a study on the assessment of health facility data from 14 countries of the Eastern and Southern Africa region showed median report completeness of 95% (34). A lower completeness of related indicators report was reported in South Africa with a value of 50.3% (35). A study was done on maternal and newborn indicators in Nigeria, Gombe state, also found report completeness of 40% (33). Likewise, another study in Ethiopia on maternal and child health indicators found low report completeness, ranging from 33.5 to 75.8%(8). The high completeness score in this study could be since all facilities reviewed were governmental facilities. Several studies' results showed, regarding data quality, public facilities perform significantly better than privately owned facilities. In addition to this, introduction of web-based RHIS in the study area have also contributed to data quality especially for report completeness.

For data to be of good quality, not only has to be accurate and consistent but also should have to avail on time. Nevertheless, in this study, from the assessed data quality dimensions, timeliness of reports was found to be the lowest where only half of the facilities submitted their report on-time. Even in some facilities reports were submitted after deadline day in all reviewed months.

The explanation for the lower timeliness of the report could be due to this study using DHIS2 generated timeliness score. DHIS2 considers the last date of data edition for a given month report timeliness calculation. However, a study conduct in Nigeria on data quality of indicators using the DHIS2 report 84% timely submission of monthly reports (33). The low timeliness of the report is indicative of a lack of a PMT. PMT is a team of the multidisciplinary health workforce that is primarily responsible to improve data quality and use of information regularly. Members meet on a monthly basis before the report is submitted to the next level to monitor progress and improve performance (36). A study done in Addis Ababa reports that all sampled health centers had PMT. However, the descriptive part of the study exposed there were gaps in the consistency of the meeting (37). Likewise, in this study, all sampled health centers have PMT and logbook assessment results shows, from the selected three months for review, all health centers had at least two recorded meetings. However, the qualitative part of this study revealed that PMTs were not functional. Most of the reports were submitted without content review where even massive data errors that could be spotted by eyeball scanning were observed during analysis. This has a huge impact on data quality especially for the timeliness of reports where multiple components of reports were adjusted after feedbacks received from higher levels after the facility already summated monthly reports.

Feedback, supervision, and data quality review are crucial to improving data from RHIS (38–41). Studies specifically considering web-based reporting systems noted that, while digitalizing of the reporting systems can improve the completeness and internal consistency of reported data, feedback and supervision remains essential for achieving and maintaining improvements in data quality (42–45).

The shortage of skill among health workers remains challenging in many sub-Saharan countries (46–48). A study from North Gondar, Ethiopia, also reported only 23.8% of staff received HMIS related training(1). However, in this study 49.5% of staff and 98.4% HMIS focal persons are trained. The difference could be due to Addis Ababa University's capacity building and mentorship project support to the regional health bureau. Like this, another study in Addis Ababa has also reported that all HMIS focal persons were trained (37). However, despite those efforts on capacity building, data quality still need improvement. This might be due to health professionals' attitudes toward RHIS activities. Health professionals are more likely to give attention and time to clinical duties and tend to pay less attention to activities related to HMIS. Findings from this study also support this argument where 52.72% of health professionals did not consider data recording as their duty.

Although DHIS2 is introduced in Ethiopia in 2018, most of the data management is paper based. Daily services provisions are recorded on government-approved registers. Staff in each department are expected to complete these registers which are then aggregated into monthly summary forms at the end of the month. That is why 58.69% of staff included in this study feel recording and collecting data is a burdensome activity. This study also finds the introduction of additional new register books from different partners, which affects the burden of the report by health workers. This would have an impact on the quality of the data. Previous studies also highlighted motivation and perception of staff to HIS tasks have a substantial link up with data quality(49–51).

Although the study was conducted in health centers sampled from all sub-cities, in this study private facilities and public hospitals were not included. In this study incorporating a comparison of data from RHIS with population survey results could have given further insight into the consistency of routine health data.

Conclusion

Assessment of routine data quality in Addis Ababa Health centers have shown good source document and report completeness. However, Overall data quality was found to be below the national expectation level. The accuracy and timeliness of reports generated from DHIS2 still need improvement.

Skill, motivation, and attitude of health professionals toward RHIS activities are behavioral factors identified as affecting the RHIS data quality. Organizational determinants such as lack of supervision, a poor culture of data quality assessment, and weak PMT meeting are also identified as factors affecting the RHIS.

Enabling the existing PMT to be functional through supportive supervision is a key to improve those gaps. Building a skillful and motivated workforce have also a substantial role in the betterment of data quality generated from the RHIS. Standardizing source documents as short-term and transforming the paper-based service registration to an electronic-based medical recording system in long term will reduce the burden on the health staff in compiling data. Reducing the workload will ensure improvement in data quality.

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