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Impact of Performance-Based Financing Implementation on Healthcare Data Quality of Health Management Information System in Sierra Leone

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Abstract

Data quality is an important aspect of data for effective healthcare planning and decision making. The Government of Sierra Leone launched the performance-based financing (PBF) scheme in June 2011, whereby target indicators included improving the quality of data for an informed decision making. We investigated the impact of PBF scheme on healthcare data quality using mixed-method sequential explanatory research design considering three data reporting periods: the pre PBF scheme in 2010, during PBF scheme in 2012, and the post PBF scheme in 2018. Results on timely reporting rate show an average percentage improvement in 2012 by 1.9% and 6.7% compared to 2010 and 2018, respectively. Results on complete reporting rate show an average percentage improvement in 2012 by 2.8% and 6.2% compared to 2010 and 2018, respectively. Results on accurate reporting rate show an average percentage decrease in 2012 by of 5.6% and 8.4% compared to 2010 and 2018, respectively. The results were validated and shown to be statistically significant, implying that the PBF scheme had positive impact on timely and complete data quality dimensions, but on the contrary, negative impact on the accuracy data quality dimension. Quantitative results strongly correlate to the mixed views on PBF obtained from qualitative results.

1. Introduction

Performance-Based Financing (PBF) is a global initiative towards attaining universal health coverage (UHC). The UHC intended to ensure, among other things, all people have access to the full range of quality health services they need, covering the full continuum of essential health services, from health promotion to prevention, treatment, rehabilitation and palliative care [1]. Performance-based financing (PBF), often referred to as pay-for-performance (P4P) or results-based financing (RBF), refers to payment to a government, organization, or individual conditioned on taking measurable actions toward achieving desired goals. Influenced by the support of different donors, many low- and middle-income countries have used PBF in an effort to improve quality, availability, and uptake of health services [2]. The Government of Sierra Leone launched the PBF scheme in June 2011 with the aim of improving healthcare service delivery of the vulnerable groups (women and children), whereby target indicators included improving the quality of data for an informed decision making [3]. The PBF scheme involved the payment of incentive or bonus to health care providers (HCPs) as means of motivating staff to provide quality healthcare services to a targeted group of people. Payments are linked to outputs measured by the quantity of services provided and the attainment of pre-identified indicators or activities [4,6,7,9,10]. PBF is designed on the premise that linking incentives to performance will contribute to improvement in access, utilization, equity of health services and provision of quality healthcare information [3,8].

The PBF implementation had steady expansion over the past years since the number of African countries using PBF increased from 4 to 21 between 2006 and 2013. By June 2017, over 32 out of 46 sub-Sahara African countries utilized PBF to promote health system reform from resource–based to result-based acquiring method [4,5,11]. A PBF scheme in Rwanda lead to an increased service delivery and quality of care, highlighting a success story of PBF on accountability and establishment of transparent procedures for monitoring progress [12,13]. This implies that healthcare financing is an important pillar and a building block in the reform package which strengthen essential health services deliveries, human resource for health (HRH) and health management information system (HMIS) [14]. The considerable increase in international funding for health have been accompanied by an increased demand for information to accurately track health progress and performance, evaluate impact, and ensure accountability at country and global levels [15]. The provision of funding by major donors for the implementation of Performance or Results Based Financing (P/RBF) mechanisms has created further demand for timely and reliable data for an informed decision making. Data management is a crucial issue for the implementation of PBF as is essential for monitoring, evaluation, verification, payment of incentives and improving the delivery of healthcare services [10]. However, poor quality data reporting is a key barrier for health management decision-making at any level [16].

Although different researchers have established that PBF implementation improves healthcare service delivery [12,13,17,18], broadly, the results-based and economically driven interventions such as PBF do not, on their own, adequately respond to patient and community needs, upon which health system reform should be based. In particular, Ireland et al. [19] argue that the debate surrounding PBF is biased by insufficient and unsubstantiated evidence that does not adequately take account of context nor disentangle the various elements of the PBF package [19]. A similar precaution is observed by de Walque and Kandpal [20], as they reviewed evidence of health financing for effective coverage and observed improvement in healthcare utilization but not quality. It is argued that, to improve quality of care, health financing should pivot from performance-pay while retaining the elements of direct facility financing, autonomy, transparency and community engagement. Fox et al. [21] conducted a study in DRC and encountered that, for

PBF to be effective, it needs to be rooted in wider financing and human resource policy reforms. Further, El-Shal et al. [22] conducted a study in Egypt and assessed the impact of discontinuation of PBF in primary healthcare, but no significant effects are reported for directly targeted outcomes. Other studies have focused on assessing PBF in the context of health workers efforts, efficiency and motivation in providing targeted health services. For example, Bertone et al. [7] examined impact of PBF on the overall remuneration of health workers in rural Sierra Leone. Shen et al. [23] assessed the effects of PBF on health workers in Zambia and found a significant increase in job satisfaction and a decrease in attrition, but had no significant effect on motivation. Lohmann et al. [24] assessed how PBF affects health workers' intrinsic motivation in Malawi and established that, to maximize positive PBF effects on intrinsic motivation, we need to inject explicit strategies into PBF designs to mitigate unintended negative impact of unavoidable design, implementation and contextual challenges. Apart from assessing the PBF impact from the context of improvement of healthcare delivery and health workers effort, no attention has been given to impact issues on data quality management despite its pivot role in supporting the overall better planning and decision for healthcare programs. This is important because effective planning for disease prevention and control requires accurate, adequately-analyzed, interpreted and communicated data [25] but little is known about the impact of PBF on healthcare data quality in low- and middle-income countries (LMICs), including Sierra Leone.

The essence, availability and accessibility of quality data should not be overlooked as it constitutes the backbone of healthcare service delivery, program implementation and evaluation. High quality data are also required to accurately evaluate the impact of public health interventions and measure public health outcomes [26]. The healthcare data are facts collected from service users (patients) by healthcare providers (nurses and doctors), which include administrative and clinical data collected on daily (routine) basis through HMIS data collection tools, such as registers and tally sheets. Quality data involve 'facts' with less or no error, unbiased, impartial, available at the time needed and can be easily retrieved or obtained, and it is restricted to maintain its security value and fit for use [27]. A single aspect of data quality is defined as a dimension; several of these are used to characterize the quality of data. It has been argued that, out of 50 dimensions of data quality, only 11 are categorized as the main dimensions of which completeness, recency (timeliness) and correctness (accuracy) in this order are the three most regularly used and common data quality dimensions [28]. Scholars and researchers confirmed that these three are the most commonly used fundamental factors of quality data [26,28,29]. Timeliness is the extent to which the data is sufficiently up-to-date for the task at hand. It is confirmed by authors that timely data reporting implies that data should be available at a useful frequency, should be current and should be timely enough to influence management decision making [27,31]. Completeness is the extent to which data is not missing and is of sufficient breadth and depth for the task at hand [27]. Note that there should be no missing data as all part of the form should be completed [32]. Accuracy is the closeness of agreement between the actual data value and its original value [27]. This study investigates the impact of PBF on data quality for routine health data an important component of the HMIS data. This is significant to the Sierra Leone's Ministry of Health and Sanitation (MoHS) policy and decision-making bodies that highly depend on quality healthcare data or information generated from routine healthcare delivery services at all health facility levels. This data must be made available and accessible at all times, and should be complete, accurate and timely reported [10].

2. Method

The study used a retrospective mixed method design with sequential explanatory research design where the quantitative data was collected and analyzed followed by qualitative data collection and analysis to explain the quantitative data. The use of both approaches helped to confirm the quantitative results with qualitative data by following up participants, have them explain the prior obtained quantitative results through a qualitative exploration of their knowledge, ideas/opinions and perceptions in relation to motivation and challenges related to data management and the PBF scheme. Secondary data collection was carried out by reviewing peripheral health unit (PHU) summary forms reported each month to the District Health Management Team (DHMT) along with documents such as registers and summary reporting forms used at the PHU level. Semi structured questionnaire based on Likert scale were administered to sampled population to gather follow-up information on impact of PBF to data quality management. In-depth interviews were further conducted to target staff at both Directorate of Planning Policy and Information (DPPI) and DHMT offices to obtain views and perceptions on the PBF effect on data quality related issues.

Different data analysis strategies were employed, including examination of secondary data from past routine data documents such as registers and summary reporting forms to analyze the quality of data that were reported by the PHU staff. Statistical analysis was further used for quantitative data descriptive analyses, trends analyses, and statistical significance tests. The software tools, such as Microsoft Excel and the Statistical Package for Social Sciences (SPSS) version 20, were used to support the statistical analyses. Content analysis was used to analyze qualitative data, which involved reading and reviewing each interview transcript and audios recorded to determine major themes related to views and perceptions regarding specific PBF effects to data quality.

2.1 Sampling and Approach

The study was conducted in the Western region in Sierra Leone as the region hosts the national DHIS database office (DPPI), and at Bo district where the main health office (DHMT) responsible for the provision and distribution of HMIS logistics, including data collection and reporting tools, is located. The selection of Bo district is also motivated by availability of all required summary reporting forms data and other characteristics including being one of the earliest districts that introduced PBF having the highest number of peripheral health units (PHUs) that implemented the PBF scheme compared to other districts. Geographically, the district is centrally located, therefore, easily accessible and has high population

Table 1. Sampling at the study area of Bo District in Western Sierra Leonne.

Sampling Aspect	Population	Sample size	Rationale
Chiefdoms	15	12	Accessibility, number of facilities implementing PBF
PHPUs	110	39	Based on urban rural mix (10 urban and 29 rural) and staff composition, for primary and secondary data collection
Questionnaire participants	141	104	The sampling formula n = $\frac{N}{1+N(e)^2}$ as in [30]. N=141, 95% confidence level, e (the level of precision) = 0.05
Interviews participants	141	35	Purposely sampled knowledgeable data managers at DPPI and DHMT (10) and knowledgeable HCPs staff (25)

density [33]. The main sampling approach is summarized by Table 1.

The secondary data were collected from the 39 sampled PHUs, DHMT and DPPI based on three target snapshot periods for the years 2010, 2012 and 2018, for six months of July to December, which signify the before, during and after PBF scheme periods, respectively, to enable cross-periods data quality performance comparative analysis. The target snapshot instances are purposely sampled to uncover the retrospective trend of data quality in the target years in order to compare performance of data quality under PBF scheme and out of PBF scheme and draw conclusion on PBF impact to data quality, which can potentially be generalized to other PBF implementing countries, especially LMICs.

2.2 Data Quality Assessment

Data quality assessment entailed a methodology that describes the methods and procedures used to assess and measure quality or values of the indicators and quality attributes [28, 29]. Gray and Weng [29] reviewed the strategies for assessment of data quality dimensions and established seven broad categories of methods, many of which are used to assess multiple dimensions (Figure 1) against the top five most commonly assessed quality dimensions, in which the weight of the edge connecting a dimension and method indicates the relative frequency of that combination. The *data element agreement* method involves comparing two or more elements within HMIS tools to see if they report the same or compatible information. The *element presence* method involves determining as to whether or not desired or expected data elements are present. The *log review* method involves examining information on the actual data entry practices such as dates, times, or edits. The study adopted three methods, namely log review, data element presence and data element agreements, for the assessment of timeliness, completeness and accuracy data quality dimensions, respectively.

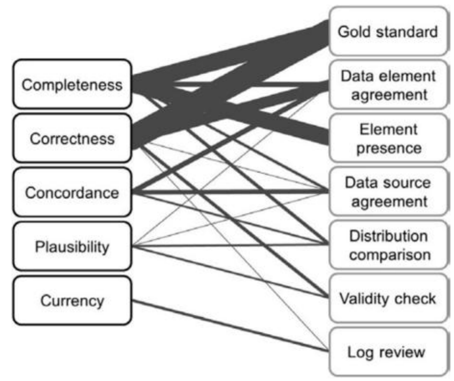

Figure 1. Mapping data quality dimensions (left) versus respective assessment methods (right) [29].

The log review method was employed to assess timeliness, in which the date of submission of reported summary forms to the district health office, verified with the date in the ledger that record reports made monthly by the PHU staff, were examined against the deadline of reporting. Forms that were received after the 5th date of every month (deadline) were considered as late reporting. Data completeness was assessed by element presence method that establish whether there are any gaps in the data from what was expected to be collected to what has been actually collected, considering all rows and columns that required filling [31]. Reported summary forms were examined for completeness using a rule out ledger into which monthly reports are entered, and the percentage of unknown or blank data is established. On the other hand, accurate data reporting is achieved when the data value recorded for a data element in the register (source document) is the same data value in the tally sheet and summary reporting forms for that specific month. Thus, data element agreement method was employed to assess data accuracy, in which the value of data elements in registers were compared to the values in the corresponding reporting forms.

3. Results

Three key players pertaining to data quality and the PBF scheme were identified: healthcare providers (HCPs), monitoring and evaluation (M&E) officers, and data entry officers (DEOs). The HCPs are government employees/medical personnel consisting of doctors, nurses, CHOs, CHAs, and midwives, among others, responsible for the collection of both clinical and administrative data from beneficiaries and do the necessary entries into the specific registers. At the end of a month, they should prepare a summarized report, enter into the various reporting forms and hand-over to the DHMT via M&E unit on or before the 5th of every month, (deadline for reporting). The role of the HCPs is vital in data quality value chain as they are the frontline data handlers. The M&E officers are data managers who provide basic monitoring and supervisory duties in the service provision, data generation and reporting. The DEOs are the custodian of the data who perform the necessary data entries into computer and upload the data into DHIS2 on or before the 15th of every month. They also provide vital services to ensure quality data is provided for top management decision making. The demographic and social characteristics of the 104 study participants is summarized by Tables 2 and 3.

Table 2. Participants education profile.

Education	Percentage (%)
Postgraduate	8
Graduate	12
Diplomas	15
Corticate	65

Table 3. Participants job title's composition.

Job Title	Percentage (%)
Community Health Officer (CHO)	26
M&E Officer	13
DEO	1
MCH/Aides	32
Community Health Assistance (CHA)	7
Disease Surveillance Officer (DSO)	2
District Operations Officer (DOO)	2
Vaccinator – EPI Assistance	2
State Certified Midwife (SCM)	6
State Enrolled Community Health Nurse (SECHN)	9

The health facility-in-charges or deputies were routinely responsible to collect, record and report information on rendered health services, commodities/equipment supplied, referrals and deaths, among others. The collected routine data are captured and entered into the health facility registers (source document) and tally sheets on a daily basis. At the end of the month, entries in the source registers are collated and aggregated into eight different peripheral health unit forms (PHUFs) that outline the HMIS summary reporting forms (PHUF1 to PHUF8) for routine health data (Table 4).

Table 4. HMIS Summary Health Facility Reporting Forms (PHUFs) for routine health data (Source: HMIS, 2008).

Form No	Name of the forms	Uses or Functions
PHUFI	Out-Patient Morbidity	The form is used to capture information regarding patient morbidity (diseases) diagnosed following consultation e.g., Malaria tested with RDT and treated, diarrhea, Typhoid etc., it deals with all ages and sex.
PHUF2	Child Health Preventive Services	The form specifically deals with children less than two years, regarding all vaccination or immunization that the child had taken and suppose to take both at the health facility and outreach.
PHUF3	Reproductive Health Services	The form gives report specifically on women in pregnancy (ANC), deliveries conducted and postnatal care (PNC), Tetanus Toxoid (TT) immunization in pregnancy and common illnesses in pregnancy

PHUF4	Form for Commodity Stock	The form deals with drugs and commodities supplied and utilized in the facility for each reporting month.
PHUF5	Deaths	Captures all deaths that occurs at the health facility and reported in the community.
PHUF6	Community Interventions	Outline and give reports on activities carried out by the community health workers in their respective communities.
PHUF7	PHU Semi-Permanent Data	This form bears reports on the cadre of personnel (human resource) and the infrastructure available at that health facility during the reporting month.
PHUF8	Report on TB. /Leprosy and HIV	TB/Leprosy and HIV contained reports on the number of cases suspected, diagnosed, treated and referred for this condition, captures any defaulter or relapse cases in these conditions.

The PHUFs are tools used to report both clinical and administrative data collected at health facilities and are reported on monthly basis to DHMT office on or before the deadline (5^{th} of every month). The PHUs data from daily registers and PHUFs summary forms covering the six months of July to December for the years 2010, 2012 and 2018 were collected from the 39 sampled PHUs for data quality assessment. Note that each summary form had corresponding register as the source document and tally sheets from which patients and clients' data were recorded.

3.1 Timeliness Dimension Assessment

The timeliness of reporting was calculated as the ratio between the total number of forms reported on time and the total number of forms expected to be reported for the target periods of July to December; 2010, 2012 and 2018, respectively (Figure 2).

The timely reporting rate trend in Figure 2 shows marginal but consistently high timely reporting rate for the during PBF scheme in 2012 that can be attributed to as a result of payment of performance incentive that served as a motivation. Taking the average for the reporting period of six months, we observe an average timely rate of 97.7% for 2012, 95.8% for 2010 and 91.0% for 2018, which imply an increased timely rate quality performance for the during PBF scheme by 1.9% and 6.7% against the pre PBF and post PBF period of 2010 and 2018, respectively. A statistical analysis to validate the results significance used the descriptive statistics data obtained from the quantitative analysis presented in Table 5.

To affirm the significance of observed trend difference, the repeated measures ANOVA test was conducted. The within-subjects factor method or repeated measures ANOVA was selected to perform analysis because the same HF forms were used in all the three years or levels.

The assessment was done under hypothesis that "H1: PBF scheme improves on data timely reporting". The repeated measures ANOVA result, as presented by Table 6, shows that the means 96.0 and 97.5 are not significantly different at 0.05 level. This is because the Sig.b (significance value) of 0.320 is greater than the p value of 0.05 in the (I=1, J=2) or (I=2, J=1). Moreover, the results confirm that the means 97.5 and 91.0 are significantly different at 0.05 level. This is because the Sig.b of 0.028 is less than the p value of 0.05 in the (I=2, J=3) or (I=3, J=2). Hence, the repeated measures ANOVA T-test validate that PBF intervention improved on the timeliness quality dimension, yet there was no significant difference between the timely rate in 2010 and 2012.

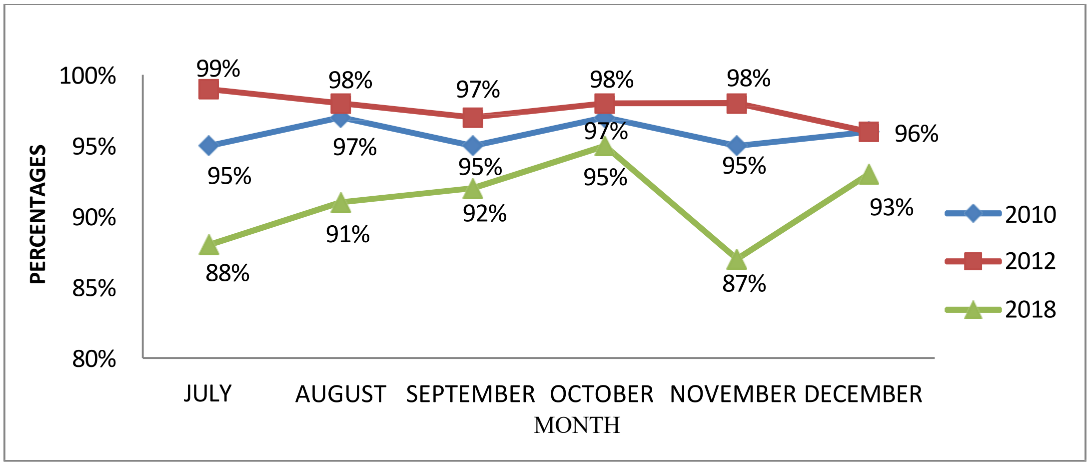

Figure 2. Percentage trends of timeliness rate for July to December.

Table 5. Descriptive statistic for data timeliness.

TIMELINESS	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
1	96.000	0.516	94.673	97.327
2	97.500	0.428	96.399	98.601
3	91.000	1.238	87.817	94.183

3.2 Completeness Dimension Assessment

The completeness rate of reports was calculated as the ratio between the total numbers of completed forms (PHUF1 to PHUF8) reported 'Y' and the total numbers of forms expected to be reported during corresponding month of the year under investigation. Figure 3 presents the percentage completeness rate trend of PHUs for the period under consideration. A notable improvement in completeness rate is observed during PBF period compared to pre PBF in 2010 and post PBF in 2018 periods, respectively. The improvement in completeness rate can be attributed to as a result of more effort and care taken to do the reporting to attract more incentive attached to performance. The six months average completeness rate for 2012 was 99.5%, for 2010 was 96.7% and for 2018 was 93.3%, which imply an increase in completeness rate by 2.8% and 6.2% during PBF scheme in 2012 compared to 2010 and 2018, respectively.

To validate the significance of observed difference, the repeated measures ANOVA test was conducted under the hypothesis that "H2: PBF scheme improves completeness rate in data reporting", using derived descriptive statistics depicted by Table 7.

The repeated measures ANOVA result presented in Table 8 show that the means 96.67 and 99.5 are significantly different at 0.05 level. This is because Sig.b of 0.006 is less than the *p* value of 0.05 in the (I=1, J=2) or (I=2, J=1). Analogously, the results show that the means 99.500 and 93.333 are significantly different at 0.05 level. This is because Sig.b of 0.009 is less than the *p* value of 0.05 for the set of (I=2, J=3) or (I=3, J=2). Hence, the repeated measures ANOVA validates that PBF scheme had a positive effect for improving completeness rate, thus, rejects the null hypothesis that "PBF does not improve completeness on data".

Table 6. Significance Test (T-Test) results for data timeliness.

Measure: MEASURE_1

Repeated Measures ANOVA / Pairwise Comparisons

(I) TIMELINESS	(J) TIMELINESS	Mean Difference (I-J)	Std. Error	Sig.a	95% Confidence Interval for Differences Lower Bound	Upper Bound
1	2	-1.500	0.764	0.320	-4.199	1.199
	3	5.000*	0.931	0.009	1.710	8.290
2	1	1.500	0.764	0.320	-1.199	4.199
	3	6.500*	1.586	0.028	.893	12.107
3	1	-5.000*	0.931	0.009	-8.290	-1.710
	2	-6.500*	1.586	0.028	-12.107	-0.893

Based on estimated marginal means

*. The mean difference is significant at the 0.05 level.

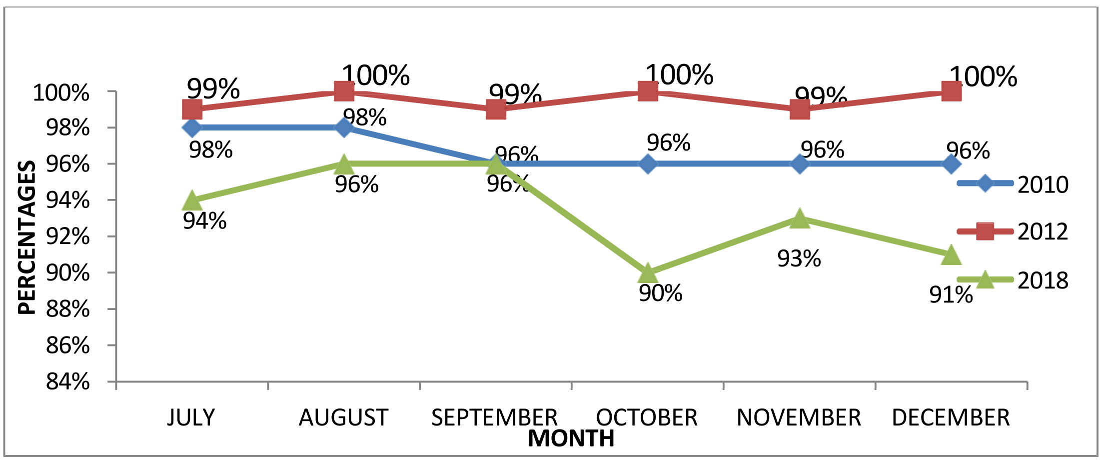

Figure 3. Percentage trends of completeness rate for July to December.

Table 7. Descriptive statistics for data completeness.

COMPLETENESS	Mean	Std. Error	95% Confidence Interval Lower Bound	Upper Bound
YEAR 2010	96.667	0.422	95.583	97.751
YEAR 2012	99.500	0.224	98.925	100.000
YEAR 2018	93.333	1.022	90.706	95.960

Table 8: Significance test results on data completeness.

Repeated Measures ANOVA / Pairwise Comparisons						
					95% Confidence Interval for Difference	
(I) COMPLETENESS	(J) COMPLETENESS	Mean Difference (I-J)	Std. Error	Sig.a	Lower Bound	Upper Bound
1	2	-2.833*	0.477	0.006	-4.520	-1.147
	3	3.333*	0.882	0.039	0.217	6.450
2	1	2.833*	0.477	0.006	1.147	4.520
	3	6.167*	1.138	0.009	2.146	10.188
3	1	-3.333*	0.882	0.039	-6.450	-0.217
	2	-6.167*	1.138	0.009	-10.188	-2.146

Based on estimated marginal means
*. The mean difference is significant at the 0.05 level.

3.3 Accuracy Dimension Assessment

The data accuracy was assessed by comparing data value in the respective registers (source document) to that of the summary reporting forms for the target months and years under investigation. The PHUs identified with accurate were added for each month. The accuracy rate of reports was calculated as the ratio between the total numbers of PHUs identified with accurate reports and the total numbers of PHUs assessed for corresponding month and year under investigation. Figure 4 presents the percentage trend for data accuracy rate during months of July to December, 2010, 2012 and 2018. We observed an irregular accuracy rate trends performance across the considered months and years, with lack of consistent margin of improvement during PBF scheme, which show lack of positive effect on PBF scheme to influence the accuracy rate of data reporting. The average percentages of accuracy rate over the six months of reporting for the considered years are 27.2% in 2010, 25.0% in 2012 and 33.3% in 2018, in which the average percentage accuracy rate for 2012 was the lowest. The average percentage decrease in accuracy rate during PBF in 2012 was by 5.6% and 8.4% compared to pre PBF in 2010 and post PBF in 2018 periods, respectively. To validate the results, a statistical analysis using the repeated measures ANOVA test was applied to validate the

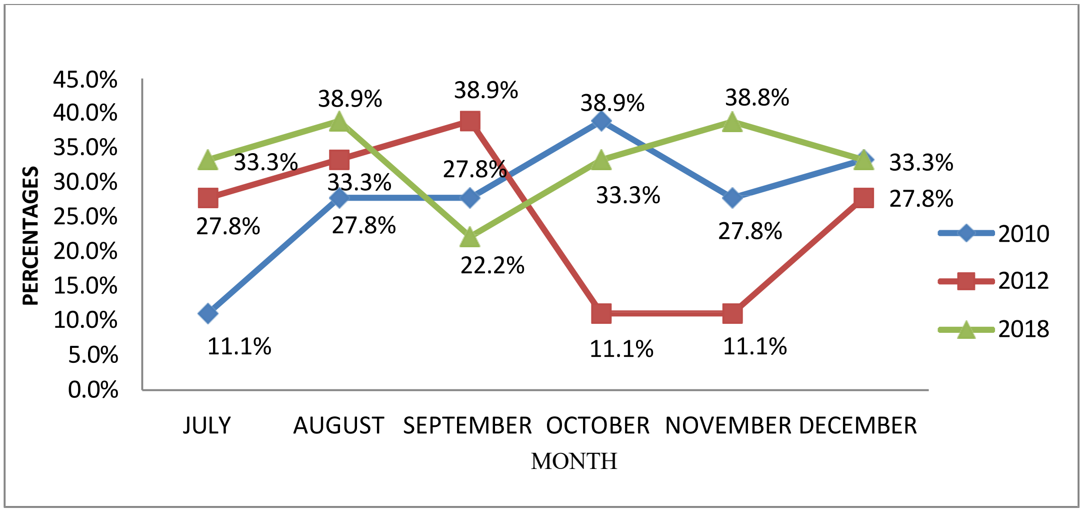

Figure 4. Percentage trends of accuracy rate for July to December.

significance of observed accuracy rate underperformance during PBF period in 2012 based on respective descriptive statistics of data accuracy presented in Table 9.

The hypothesis that "H3: PBF operation does not improve on accurate data reporting" was established. The results presented in in Table 10 show that the means 27.783 and 25.0 are not significantly different at 0.05 level. This is because Sig.a (significance value) of 1.0 is greater than the *p* value of 0.05 for the set of (I=1, J=2) or (I=2, J=1).

Table 9. Descriptive statistics of accurate data reporting.

			95% Confidence Interval	
ACCURACY	Mean	Std. Error	Lower Bound	Upper Bound
YEAR 2010	27.783	3.796	18.025	37.542
YEAR 2012	25.000	4.705	12.905	37.095
YEAR 2018	33.300	2.482	26.920	39.680

Table 10. Significance test results of data accuracy.

Repeated Measures ANOVA / Pairwise Comparisons						
					95%Confidence Interval for Difference	
(I) ACCURACY	(J) ACCURACY	Mean Difference (I-J)	Std. Error	Sig.a	Lower Bound	Upper Bound
1	2	2.783	6.995	1.000	-21.937	27.504
	3	-5.517	4.536	.834	-21.546	10.513
2	1	-2.783	6.995	1.000	-27.504	21.937
	3	-8.300	6.371	0.748	-30.814	14.214
3	1	5.517	4.536	0.834	-10.513	21.546
	2		6.371	0.748	-14.214	30.814

Moreover, the results show that the means 25.0 and 33.3 are not significantly different at 0.05 level. This is because the Sig.b (significance value) of 0.748 is greater than the p value of 0.05 for the set of (I=2, J=3) or (I=3, J=2). Hence, the repeated measures ANOVA validates that PBF intervention had not improved the accuracy in data reporting but to the contrary. Hence, the alternate hypothesis, which states that PBF intervention can improve on accurate data reporting, is rejected.

3.4 Perceptions and Views on the PBF Scheme

The result from semi-structured questionnaires provided insights on participants' views and opinion on PBF scheme influence to specific factors linked to data quality (Table 11). Overall, a high level of
agreement was observed among participants that the PBF scheme had positive effect on key factors that also influence good quality data and staff efforts.
The follow-up in-depth interviews uncovered further views and perceptions over specific issues related to PBF investments (Table 12).

Table 11. Perception on PBF scheme influence on factors linked to data quality.

	% Level of Agreement	
Factor	Large Extent	Very Large Extent
PBF promotes teamwork	24	73
PBF incentive encourages staff effort in data collection	19	78
PBF motivation encourages timely reporting	30	70
Timely reporting prompt effective payment of PBF incentive	27	65
PBF promotes data completeness	22	78
PBF promotes accurate data decision making	5	95
PBF sustained staff attendance	19	73
PBF promotes more effort to data processing	27	68
PBF promotes effective data collection and reporting	19	76

Table 12. Emerged views and perceptions from in-depth interviews.

Positive effect views/perception	Potentially negative effect views/perceptions
Enabled the HCPs to report timely to DHMT /DPPI	Performance measured at facility level rather than at individual level
More supportive supervisory visits (monthly and quarterly) by DHMT/DPPI	Incentive sharing done by cadre and paid at facility level
Regular feedback by DHMT/DPPI on previous reports	Discrepancies in data reporting – registers vs summary forms
Improved data collection and availability of data collection tools at PHUs	Lack adequate knowledge in data management
Encourage team work in processing summary reports	Inflated figures to earn more incentive
Promote immunization coverage and reporting	Irregular payment of bonus/incentive
Motivation and performance of staff	High flow of patients and clients may also result to poor quality of care
Increased number of patients and clients receiving services	

The general consensus that emerged from the results in Tables 12 and 13 demonstrates the effect of PBF scheme to steadily improve data quality, especially with respect to completeness and timeliness of reporting, as payment of incentive was more dependent on the reporting of the data parameters. Nevertheless, results from Table 15 provide views/perceptions that may had negative effect to data quality, such as the possibility that some PHUs may had intentionally inflated PBF indicator figures in an attempt to unscrupulously receive more PBF incentive. The PBF true extent of improvement in the quality of data cannot be underscored based on views/perceptions only.

4. Discussions

Although different efforts have been invested in strengthening health management information systems (HMIS) in Sub-Saharan Africa to improve accessibility of quality data to decision-makers, there are high variations in the tool utilization and data accuracy at facility and district levels [25]. This study aimed to investigate the PBF intervention effect on data quality focusing on three commonly studied quality dimensions of timeliness, completeness and accuracy. The quantitative analysis results showed with significance that the PBF scheme had positive effect for improving the timeliness and completeness quality dimensions but negative effect on the accuracy quality dimension. The quantitative results strongly correlated with the qualitative results obtained from analysis of views/perceptions, which portrayed both positive effects on factors linked to data quality improvements, but also uncovered negative effect factors linked to impair data quality. For example, the fact that performance was measured at facility level rather than at individual level and incentive sharing was constrained by cadre and paid at facility level, hence, less level of effort recognition to the lower cadre who engage in most of the difficult and time-consuming duties (such as deliveries) and so less incentive [34], captures negative effect. Further, the fact that in some PHUs the PBF indicator figures were intentionally being inflated in an attempt to unscrupulously attract more incentive [35] signify negative effect. Malpractice in data, such as cooking falsification, had huge potential as payment of incentive was dependent on routine data collection and summary reports. The HCPs could easily be tempted to falsify data entry with the intention of making more money, but causing adverse effect on reported data accuracy. This stress the need to design specialized strategies within healthcare interventions for improving data quality. The latter observation resonates with the Mozambique PBF scheme where strong financial punishments were in place to discourage inaccurate reporting. As such, policies were in place to enforce data reporting ethics to which a difference of 10% between the reported and verified report for a particular indicator resulted in no payment for that indicator for that quarter. Specifically, a health facility would lose all PBF payment for a quarter when 10% difference is observed in three or more indicators [36].

In summary, although studies have concluded only positive effect on PBF scheme [12,13,17,18], there are quite a number of studies [20, 21, 22, 23, 24] that have shown PBF mixed effect under different contexts, which correlate with the findings from this study under the data quality effect context. For instance, Lohmann et al. [24] concluded that PBF scheme did not affect health workers' overall intrinsic motivation levels in Malawi, with the intervention having had both positive and negative effects on psychological needs satisfaction. The takeaway from the study is to re-iterate the need to undertake extensive risk analysis in health intervention plan and identify appropriate mitigation strategies to holistically balance the overall intervention outcome.

5. Conclusion

In Data quality is an important aspect of data for effectiveness in overall healthcare planning and decision making. This study assessed the impact of

PBF scheme on healthcare data quality of reported routine healthcare data in Sierra Leone. Three commonly studied aspects of data quality, namely timeliness, completeness and accuracy, were assessed and showed that the PBF scheme had positive effect on timeliness and completeness, but negative effect on accuracy. Several studies have assessed the PBF scheme impact in LMICs, albeit under different contexts, but this study is the first to explore PBF scheme impact in relation to data quality, using Siera Leone as the case. The reported mixed effects (positive and negative) on PBF scheme impact on data quality was shown to concur with numerous related studies. Therefore, we advocate the need to design strategies that can alleviate negative effects as part of intervention plan

This study is limited to assessing the data quality impact to only three key factors of quality, namely timeliness, completeness and accuracy, in Sierra Leone. We recommend future studies to expand our findings to countries, such as Mozambique, with data quality mitigation strategies to guide design of a systematic guidance or a framework for data quality in health interventions.

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CONTRIBUTIONS OF CO-AUTHORS

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