UTILIZATION OF ROUTINE HEALTH DATA IN DECISION-MAKING BY MANAGEMENT TEAMS IN SELECTED LEVEL 4 HOSPITALS IN NAKURU COUNTY, KENYA

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International Academic Journal of Health, Medicine and Nursing (IAJHMN) | ISSN 2523-5508

Received: 28th June 2023

Published: 4th July 2023

Full Length Research

Available Online at: https://iajournals.org/articles/iajhmn_v2_i1_314_340.pdf

Citation: Kagwiri, M., Otieno, G., Mawenzi, R. (2023). Utilization of routine health data in decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya. *International Academic Journal of Health, Medicine and Nursing*, *2*(1), 314-340.

ABSTRACT

Health data are the relevant information routinely collected in health institutions by health workers. The health population needs can only be identified through data collection, collation and analysis that provides information that should be used by the hospital management teams (HMT), in prioritizing resource allocation for service delivery, health work force, essential medicines, and governance. In most hospitals, these crucial managerial responsibilities seem to be lacking the support of data use for evidenced decisions, leading to poor service delivery and unnecessary referral of patients, yet the same hospitals task their health workers with data collection and monthly submission of reports. In light of this, the aim of this cross-sectional study, was to assess utilization of routine health data for decision making by HMTs of the selected level 4 hospitals in Nakuru County; Molo, Subukia, Olenguruone and Naivasha sub county hospitals. This was achieved by determining the extent of use of the data collected for decision-making and examining data quality and identifying organizational factors, influencing use of routine health data in decision making. The target population of the study was 156 Hospital management team members, selected by use of census sampling method. The study used two data collection tools; the questionnaire and the interview schedule. An observation checklist was used to identify presence or absence of list of items representing quality data and evidence of data. A pilot study was conducted on a group of 17 hospital management team members (10% of the sample size) from Langa-Langa hospital. A Cronbach reliability coefficient of 0.72 was achieved for each of the construct and thus considered reliable. Analysis for Descriptive and inferential statistics were done using Statistical Package for the Social Sciences (SPSS) version 25. The study found that Nakuru county has an average data utilization index of 62.9%, good use, and that accuracy of data collected as well as use of registers as a data collection tool were significantly associated with use of Health data at a p-value of 0.025 and 0.043 respectively. This study may act as a reference for informing the county government, on the status of the national governments' initiative and the capacity of the hospital managers in sub county hospitals in data management for appropriate intervention. The findings may also act as a spring of literature for researchers to do auxiliary studies about routine data consumption for decision making at points of data collection.

Key Words: Routine Health Data and Decision-Making by Management Teams

INTRODUCTION

Health data are the relevant information routinely collected in health institutions in an ongoing manner. Data is managed by the District Health Information System 2 (DHIS 2) a web-based software development project by the health information system (HIS) program introduced in Kenya in September 2011. The health information system is divided into five phases i.e., Information generation which is the type of data collected, tools for data collection and storage; Information validation, the process of improving accuracy and representativeness; information analysis which requires one to understand the information one collects; Information broadcasting, the process of its sharing and the last and most important is information utilization in decision making.

Routine health information system (RHIS) is the source of data for HIS as it generates data at consistent intervals through the health workers as they go about their daily work. (MEASURE evaluation, 2015). The data collected is on community status of well-being, health interventions, resources available for health, and statistics on service delivery per facility, surveillance on community - based health information, and administration data such as: revenue, costs of drugs, personnel, training, and research, which is crucial for decision making. At the global level, data estimates the burden of disease, measures progress in health and guides in containment of emerging global health threats. The same can be measured at the national level with a closer use of data in allocation of resource, its prioritization and planning while at the local level data is useful for monitoring population health and for directing interventions for the community. An analysis done by Measure evaluation in 2019 on 22/30 national health indicators exposed an outdated HMIS strategic plan, an inactive HMIS body and no guidelines for data use. The efficacy and effectiveness of any hospital is attributed to a good management system while the opposite is true. Managing a hospital is a great task and therefore, the hospital managers are required to make decisions that hold consequences for the health outcomes of individuals and communities.

Problem Statement

The need to have efficient health care services delivery at different levels of service provision has been heightened by the introduction of UHC (Universal health coverage) and its target for 2022-2030. More pressure and attention have been directed in institutions that offer primary health care such as level 4 hospitals. The Hospital management teams responsible in running the services of these hospitals, are expected to deliver high quality and affordable services for a rising sum of patients by use of data, since the current and future health care requires evidence in order to justify action. Due to perceived or existing low-quality services offered at lower levels of health care, many unnecessary referrals to level 5 and 6 hospitals continue to be witnessed. A Nakuru health taskforce report (2017-2018), on four level 4 hospitals showed that, clients often by-passed available services or were referred to seek similar services at higher levels of service care. The inability of the level 4 hospitals to manage health concerns led to an influx of patients in higher levels of health care and caused an increase in preventable mortalities and morbidities. The county referral hospital also called Nakuru level 5 hospital (NL5H) had a bed capacity of 784 with an average total occupancy of 87%. Hospital records showed some overwhelmed departments such as surgical ward at 111% occupancy, Orthopedic wards at 95% and medical wards at 108% occupancy. Referrals are at an average of 55 patients per month and mortalities at an average of 250 deaths per month. The most common cause of deaths as of 2021 analysis is pneumonia, which can be managed at level 4 on early detection. With all the resource invested on data management, (Approximately 9million as of 2018-2019 HMIS budget) it is not known how and whether the Hospital management teams utilize their facility data in decision making. Failure to assess information use, RHIS cannot be said to improve evidenced decision-making. This study therefore, sought to assess utilization of routine health data in decision making by hospital management teams in selected level 4 hospitals in Nakuru County, Kenya.

Broad Objective

To assess utilization of routine health data in decision making by Hospital management teams in selected level 4 hospitals in Nakuru County.

Specific objectives

i. To determine the extent to which routine health data is used for decision-making by management teams in selected level 4 hospitals in Nakuru County, Kenya
ii. To examine data quality factors influencing utilization of routine health data in decision making by management teams in selected level 4 hospitals in Nakuru County, Kenya
iii. To identify organizational factors influencing utilization of routine health data in decision making by management teams in selected level 4 hospitals in Nakuru County, Kenya

LITERATURE REVIEW

Routine Information Management System

The world health organization refers to health information management system (HMIS) as a continuous integrated effort in gathering, processing, reporting and using health information to persuade policy making, programmed action and research (WHO, 2011). An effectual and integrated HMIS is fundamental in upgrading the quality of health service delivery and improving health outcomes as it is the principal source of timely data and a channel for information exchange for evidence-based planning and decision-making.

Extent of Routine Health Data Use

In a bid to advance accessibility and affordability of health care to local communities, the government of Kenya through KEPH organized public hospital service provision in levels with specific type of services and then follow the referral system as stated by the MOH. (KHSSP III). In this study, the level of interest was level 4 hospitals, previously known as district and now sub-county facilities and is referred to as primary health facilities as they are meant, and are equipped to deal with preventive, promotive, curative and rehabilitative services. The question of the study was, do the decision makers utilize data in deciding on the management of the services and various activities performed in a hospital.

In a study done by Karimi (2017) in Kitui County, 34% of the health managers used data to guide decisions while 66% (73/110) health care manager did not. On various areas of decision making, 46% used data on daily program management, 37% for medical supply and drug management, 51% in formulation of patient's care, 31% of the participants reported use of data on financial statements, 35% budget allocation, 33% in management of human resource, 40%

in key health objectives monitoring and policies and 70% for identifying emerging epidemics. The same is seen in North Gondor zone, Ethiopia, where majority of the respondents in a study done to assess use of RHIS were seen to use data on several activities/decisions. The study used a sample size of 720 and 90.1% of the respondents used data for disease monitoring, 85% on pharmaceutical procurement, 89.6% on monitoring health activities, 92.6% scrutinizing data quality, 86.7% in allotment, on planning 89%, on department performance evaluation 88%, 86.5% on personnel performance appraisal and 87.1% for community mobilization. (Dagnew et al, 2018).

A similar study done in coast general hospital; Kenya by Mboro G 2017 indicated the use of data by the hospital managers as slightly above average at 69.6%. On the areas of study those who used data in management of supply and drugs were 74%, gaps identification with the aim of training at 72%, Resource mobilization were 66%, Staffing decisions at 60%, and on service delivery improvement at 67%. At Gucha Sub-county in Kisii county, a study done by Obwocha et al 2016, showed data/information utilization rate at only 30% leading to inadequate resource distribution. In Nairobi County, the estimated data use in making decisions was at 60% (Gathua, 2014) with Kenyatta National Hospital reporting of only 53.6% of nurses who utilized research findings in practice while 70.5% based their decision making on knowledge achieved during nursing school training. (Mutysia, 2015).

Contemporary health care practices, require evidence in order to justify action in meeting the varying needs of health. Health managers therefore, need to shift from conventional practices to evidenced decision making. The challenge of data use is not only confined in Kenya, according to Dagnew 2018, Health systems managers in developing countries tend to shy away from data use due to various challenges with Ethiopia showing to have performed relatively well with 78% rate of data utilization in decision making as compared to other poorly performing countries i.e. 42% data use in Tanzania, 59% in Uganda, Liberia at 58% and 65% in South Africa. Adequate research has not yet been done in Kenya for sufficient national comparison.

Data Quality Factors Influencing Data Use

The quality of data is a varied paradigm, which includes numerous dimensions, such as: accuracy, consistency, totality, timeliness and integrity. Lippeveld, (2009), discusses data quality in four ways: aptness or relevance entirety, timely and accuracy where relevance is the comparison of data collected against its capacity in managing information needs and entirety is evaluated not only as filling in all data elements in the report form used in data collection, but also as the number of facilities reporting in a region and the type of data reported. Realizing quality data is not therefore a simple task and it is exacerbated by lack of well-trained personnel and lack of clear rules and standards to guide creation of information for decision making. Indeed, in many resource-limited settings, it remains a challenge in ensuring data quality for meaningful interpretation (Ledikwe.2014).

In most hospitals in Kenya, the nurses are tasked with the responsibility of entering clinical data into prefabricate tally sheets. More often, they are overwhelmed by their demanding clinical duties and disregard the tally sheet which then goes unfilled, and this contributes to incompleteness. The data collected by untrained and busy individuals is usually poor and deficient, making it inaccurate thus affecting the decision maker's confidence in the use of data and consequently the data management (Karuri, 2014). A study done in Uasin Gichu County referral hospital by Cheburet, 2016, indicated 70% (57/82 respondents) of the data collectors were nurses and 30% (25/82) were accounts staff. 51 respondents of the same study (63%) said that the data producers were not trained while 37% said the data producers were trained. In Tharaka-Nithi County, the trend was similar with 95.2% of the respondents, who reported that casual labourers were the major data collectors in the hospitals and that they lacked computers, and were also untrained on data collection (Mucee, 2016).

According to USAID/Kenya 2010, weaknesses to data quality are distinctive to systems that depend on paper transmission, manual aggregation and analysis of data. Wamae 2015 stated that Kenya has 66% of its health data collected on paper first and then transferred to electronic system while 34% of the data is captured only on paper. Paper based data management technique is fraught with storage and retrieval problems which eventually lead to inaccurate and incomplete data. Paper based data collection poses another challenge due to proliferation of data collection tools, most of which have been developed by specific programs for their management and yet they are used in other sectors without customization. In Tharaka-Nithi County, in a study done on data use determinants, the respondents complained of inadequate data collecting tools (57%) and that the tool were too many and repetitive causing fatigue to the users leading to inaccurate data. In Coast general hospital, the respondents rated the quality of data as; 48.7% poor on timeliness, 47% poor on accuracy and 42.8% poor on completeness (Mboro, 2017). Relevant and timely data births accurate decisions and in the same breath, irrelevant data delivers irrelevant information, which adds to a confused decision-making process that, affects the output of an institution or department. Therefore, it is vital that managers are attentive to what they require, how to attain it and to capitalize on quality of data generated in their facilities to boost user confidence, in order to make informed decisions.

Organizational Factors Influencing Use of Data

According to the Kenya Health Information System (HIS) policy, a decentralized system introduced by the Ministry of Health (MOH) was to be used by all health institutions and emphasized on consumption of data at the point of collection. Such decentralization increased freedom of decision and responsibility of actions taken at each point of care, consequently, demand of more skills was heightened for the decision makers and hospital managers in relation to data handling and use to suppordecisions taken at all levels of a health care system (Gladwin, 2003).

Decision making has three elements as discussed by Nutley (2010). Data, questions and stakeholders whereby without all these components one fails to make evidence-based decision. The organization/institution is a stakeholder as it has an interest in the decision-making being made by its managers. However, there exists a conflict between data user (considered as the decision makers) and data producers (considered as the data collectors). For instance, the data users may feel that data producers lack responsiveness to health priorities and data producers may feel that data users are unprepared to measure or evaluate the consequences of their decisions. In the presence of these disagreements the information does not reach decision makers in time.

Organizational challenges noted in different health facilities were, lack of feedback on data use as seen in a study done by Mumo 2017 in Makueni County where the county feedback on data use was at 94%, lack of support from the management, for instance in Tharaka-Nithi County, Mucee, 2016 reported of 38/41 respondents in a study to have indicated lack of support of staff training, 39 (95.1%) stated lack of supportive supervision and 40 (97.6%) indicated low information culture with no attempts to improve it. In Malindi Sub County hospital, the respondents appreciated the provision of policies and guidelines on data use at 96% with only 55% acknowledging feedback from their managers regarding quality of data collected and its consumption. The availability of tools for data collection was at 58.8%, supportive supervision was seen to be low at 44.4% and even lower was the hospital funding of the HMIS activities which was at 7.2% (Chorongo, 2016).

This was similar to a study done by USAID/Kenya, (2010) that indicated there was little allocation of resources for HMIS. Yet, according to The Abuja declaration, it was agreed that HMIS was to be allocated 15%, however, Kenyan hospital's HMIS departments were generally poorly financed at 3% as indicated by Kihuba 2014. Lack of funds led to task shifting where hospitals address the deficits by using nurses and other health care workers instead of records officers to take a leading role in data collection and compilation. On the level of motivation, in coast general hospital, 129 (55.1%) of the respondents said the motivation was moderate with 12 (5.1%) reported it as high and 32 (13.7%) as low. In a focused discussion, one of the respondents pointed out that they (data producers and users) were frustrated with a lot of paper work yet there was no feedback and appreciation from the authority (Mboro, 2017). In a similar study done by Dagnew et al, 2018, in North West Ethiopia, the health workers and managers of the public health facilities that participated in the study demonstrated positive belief in RHIS use at 337 of the 720 respondents and 228 had a negative belief towards RHIS use. On custom or culture of data use, 135 respondents said it was good while 430 respondents felt the culture of data use was poor, on value placed on RHIS use, 90 respondents said it was good while 475 respondents said it was poor.

Some of the possible interventions by institutional management to improve data use as mentioned by the respondents in the coast general hospital through a study by Mboro (2017), training and mentorship of the data producers and users to enhance confidence of use (33.2%), regular feedback and information sharing to encourage the assessment of progress for improvement or reward (20.7%), systems automation to move from paper based which is time consuming to computer based for ease in analysis and retrieval after storage (13.3%), availing equipment and data collecting tools (9.4%) and hiring of HRIO for data management.

Conceptual framework

Independent variable **Intervening variable** **Dependent variable**

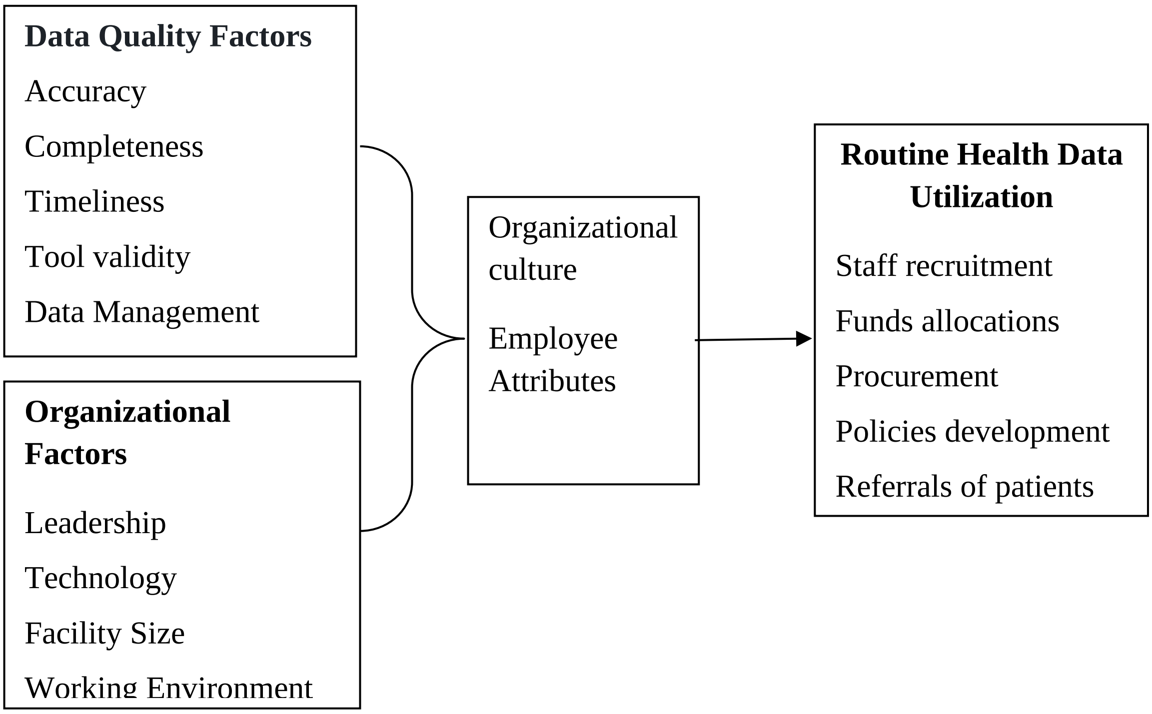

Figure 1. 1: Conceptual Framework of the Study
Source: Adapted from measure evaluation, 2010

RESEARCH METHODOLOGY

This study used a descriptive cross-sectional study design. Descriptive cross-sectional study design was appropriate because it enabled the collection of large amounts of data at one given point in time. (Sekeran, 2016). The study was conducted in four level 4 hospitals in Nakuru County namely; Subukia sub-county/level 4 hospital in Subukia constituency, Molo sub-county/level 4 hospital in Molo constituency, Naivasha sub-county/level 4 hospital in Naivasha constituency and Olenguruone sub-county/level 4 hospital in Kuresoi Constituency. These hospitals offer primary care services for patients and coordinates referrals from the smaller health facilities referred from level three, two and one facilities to Nakuru level five hospital situated in Nakuru County.

The target population of the study was 156 hospital management team members in Subukia, Molo, Naivasha and Olenguruone sub-county (Level 4) hospitals. The hospital management team members comprised of four medical superintendents, four hospital administrators, four nursing officer in-charges, four hospital accountants, four health records department in-charges, four procurement department in-charges, four human resource officers, four Laboratory department in-charges, four radiology department in-charges, four pharmacy department in-charges, four physiotherapy department in-charges, 56 head clinical departments and 56 ward in-charges. Out of the 156- study population, 146 of the hospital management team members were respondents of the study while 11 hospital management team members were key informants (Medical Superintendents, Hospital Administrators and Health Records Department In-charges).

Census sampling refers to complete enumeration of the target population into the study. This approach ensured that there was zero sampling error and improved the generalizability of the study findings to the target population. The sample was proportionately distributed across the four select level 4 hospitals in Nakuru County. Proportional distribution ensured that there was no selection bias and there was proportional representation of study subjects as they appeared in the target population (Creswell, 2014).

Three data collection tools were used; a questionnaire and an interview schedule. The questionnaire was divided into four sections. The first section entailed the background information of the respondents, second section collected data on the extent of use of routine health data, third section collected data on the data quality factors and the last section focused on organizational factors. Key informant interviews were used to provide the views and opinions of the managers (Medical Superintendents, Hospital Administrators and Health Records Department In-charges). An observation checklist was used to identify presence or absence of list of items representing quality data and evidence of data.

The study and data collection were permitted by NACOSTI and additional authorization from the four selected hospitals. The researcher applied drop-and-pick method administration where the researcher issued the questionnaires to the respondents and collected them after one week. Interviews for the key informants were scheduled and carried out on the appointed dates. The responses from the interviews were noted down in a systematic manner in a narrative form. The researcher identified the presence or absence of list of items representing quality data and evidence of data and marked accordingly on the observation checklist.

Analysis of descriptive and inferential statistics was done using Statistical Package for the Social Sciences (SPSS) version 25. Frequencies, percentages, mean and standard deviations were used for descriptive statistics while inferential statistics were analyzed using logistic regression. The results were presented in the form of tables, figures and narrative form.

RESULTS AND FINDINGS

The study sampled 156 HMT members in Subukia, Molo, Naivasha and Olenguruone sub-county (Level 4) hospitals. A total of 156 questionnaires and 11 key informants (Medical Superintendent, Hospital Administrator and Health Records Department in-charge) were administered. Of all the questionnaires administered, 146 were completed and returned for analysis, translating to response rate of 93.6%. Similarly, out of the targeted 11key informant interviews, 6 interviews were successfully conducted (54.5% response rate).

A total of 146 participants comprised of 57.5% (n=84) male respondents and 42.5% (n=62) constituted the female respondents. Majority (37%) of the respondents were aged 36-45 years while only 19.2% of the respondents were aged 26-35 years. Those aged 45-55 years were 24.7% while those aged above 55 years were 11.6% and 7.5% were below 25 years. Majority of respondents (35.6%) held higher diploma qualifications, 26.7% held undergraduate degree and 24% possessed diploma while 7.5% had master's degree and only 3 (2.1%) had doctorate (PhD) qualifications. However, there were 4.1% (n=6) hospital management team with certificate qualifications as the highest level of education. Majority (39%; n=57) of the HMT were head of clinical departments followed by 38.4% (n=56) who were ward in-charges. These accounted for over three-quarters of the HMT in the sampled hospitals. Further, 41.1% have held the position for 1-5 years, 28.8% for a period between 6-10 years, 19.9% for less than a year while 10.3% have held that position for more than 10 years.

Use of routine health data

The overall level of Routine Health Data utilization for decision making

Routine health data use was assessed using utilization index (mean) established from a set of nine areas of utilization (Table 4.3).The respondents self-rated their extent of data use, in a scale of 1 to 5 (1 never; 2 Rarely; 3 sometimes; 4often; 5 always).The rating score was from 0% to 100%, where 1 meant that the use of data was very low with a rating score of (0 – 20)%, 2 meant low with a rating score of (21 – 40)%, 3 meant data use was average with a rating score of (41 – 60)%, 4 meant high with a rating score of (61– 80)% and 5 meant very high with a rating score of (81-100)%.

According to theanalysis results shown in table 4.3, routine health data for referrals had a mean 3.84 implying that 76.7% of the respondents used routine data for referral of patients, however, a KII had a different view, "… *most of the times there is no data available or accessible to refer to when making urgent decisions such as referrals, therefore when a patient is in need of services we do not offer, we immediately refer, unfortunately, nothing is done to correct the shortcomings,….policies are made as per whoever is in office and may change with change of office bearer" (KII 06).*

On other activities,72.3% use was on supply & drug management (mean=3.62), 65.3% for staffing recruitment & training (mean = 3.26), 61.5% for outreach activities (mean = 3.08) while 61% used routine data for service improvement had a mean of (mean = 3.05). However, 55.2% (mean = 2.76) utilized routine data in policies development which recorded the lowest use followed by 55.5% of the respondents using routine data for customer feedback and 57.3% for funds allocation.

The overall routine data utilization index was calculated by taking the mean of all nine dimensions which came to 62.9%.

Table 1: Overall extent of Routine Health Data utilization for decision making

Ranking	Use area	Mean (n=146)	Rating Score (%)
1.	Referrals of patients	3.8356	76.7
2.	Supply & drug management	3.6165	72.3
3.	Staff recruitment & trainings	3.2637	65.3
4.	Outreach activities	3.0753	61.5
5.	Review strategy/Performance	3.0642	61.3
6.	Service improvement	3.0479	61
7.	Funds Allocations	2.863	57.3
8.	Customer feedback	2.774	55.5
9.	Policies development	2.7586	55.2
Routine Health Data utilization index		**3.1443**	**62.9**

Routine health data utilization for decision making

The dependent variable was evaluated by use of fifteen questions. The mean score of health management teams' extent of data use was calculated by adding up respondents' scores for each item (rated from 1 to 5) and then the total score divided by total respondents. Health management team that scored greater than or equal to the mean value of Likert scale questions (> 47.43) provided to measure routine health data use were labelled as good use of routine health data for decision making, whereas health management team who scored less than the mean value of Likert scale questions was labelled as poor use of routine health data for decision making. In this study, good routine health data utilization was found among 76(52.1%) with (95% CI: 43.6%-60.4%) of the study participants (figure 4.6). Furthermore, good routine data utilization was found among 78.6% (22) participants from Molo Level 4 hospital, while 56.4% (22) participants from Olenguruone Hospital, 53.6% (15) participants from Subukia Hospital and 52.9% (27) participants from Naivasha Hospital were found to have poor data utilization.

This was reflected on by one of the KII who said "*The culture of information use is very poor at all levels starting from level 6 hospitals to level 4 otherwise directions on areas to improve in data use would trickle down from higher facilities to lower level facilities" (KII 02).*

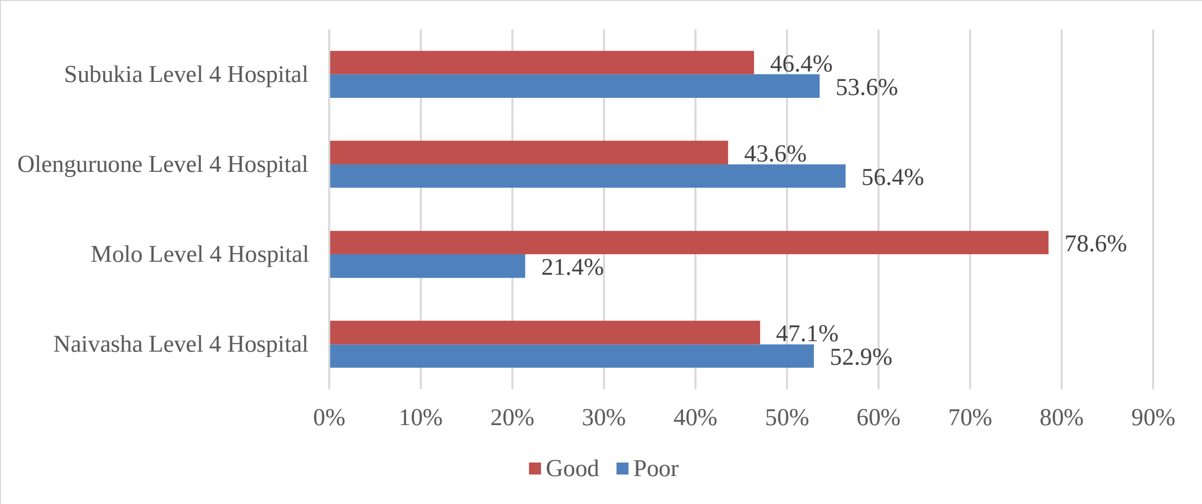

Figure 1: Routine health data utilization among the level 4 hospitals

Routine health data use and socio-demographic characteristics

Further analysis with an aid of chi-square test was carried out in order to establish association between respondent's characteristics and use of RHD for decision making. The Pearson chi-square in table 2 shows no statistically significant association between gender ($_\chi{}^2$=3.124, p=0.077), age ($_\chi{}^2$=3.124, p=0.0537) and level of education ($_\chi{}^2$=1.241, p=0.743) on the RDH use.

Table 2: Bivariate analysis of Socio-demographic factors influencing routine data utilization

Variable	RHD use		Chi-square value	P-value
	Poor (n)	**Good (n**		
Gender				
Male	35(41.7%)	49(58.3%)	3.124	0.077
Female	35(56.5%)	27(43.5%)		
Age				
Below 25 years	5(45.5%)	6(54.5%)		
26 - 35 years	11(39.3%)	17(60.7%)		
36 - 45 years	28(51.9%)	26(48.1%)	3.124	0.0537
45- 55 years	20(55.6%)	16(44.4%)		
Above 55 years	6(35.3%)	11(64.7%)		
Level of education				
Diploma & below	20(48.8%)	21(51.2%)	1.241	0.743
Higher Diploma	22(42.3%)	30(57.7%)		

Undergraduate Degree	21(53.8%)	18(46.2%)		
Postgraduate	7(50%)	7(50%)		
Health facility				
Naivasha Hospital	27(52.9%)	24(47.1%)		
Molo Hospital	6(21.4%)	22(78.6%)	9.873	0.020*
Olenguruone Hospital	22(56.4%)	17(43.6%)		
Subukia Hospital	15(53.6%)	13(46.4%)		

The differences in routine health data utilization per health facility was noted to be statistically significant at a p =0.020 as shown in table 2.

Data quality factors influencing RHD use

The data quality factors were measured by five-item Likert scale questions ranging from '1= Never '5= Always'.

Table 3: Model Coefficients for Data Quality and Data Utilization

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-0.196	0.239		-0.820	0.413
	Data Quality	1.052	0.075	0.763	14.104	0.000

a. Dependent Variable: Data Utilization

The study established that data quality was a significant predictor of extent of data utilization due to a p-value of less than 0.05. It was noted that one unit increase in data quality aspects resulted into 1.052 units increase in data utilization and vice versa with other factors held constant. This implied that data quality positively influenced the extent of routine health data use in decision making by management teams in selected level 4 hospitals in Nakuru County, Kenya.

Of all respondents, 121(82.9%) respondents believed that the data collection tool captured data on all services offered in the health facility and 78(53.4%) of health management team responded that the data is current, accurate and adequate. About 64(43.8%) of the respondents indicated that the health facility ensured routine health data was complete before analysis while 46(31.5%) agreed that health routine data was available when needed. Only 86(58.9%) participants believed that data management is undertaken in their health facility. Table 4.6 shows the summary of the level of agreement by the health management team on the level accuracy, completeness, timeliness, tool validity and data management in the health facility.

Table 4 : Extent of data quality factors

Variable	*Number*	*Percent (%)*
Tool Validity		
Yes	25	17.1
No	121	82.9
Accuracy		
Good	78	53.4
Poor	68	46.6
Completeness		
Good	64	43.8
Poor	82	56.2
Timeliness		
Yes	46	31.5
No	100	68.5
Data Management		
Good	86	58.9
Poor	60	41.1

Figure 2 below shows the extent of data quality factors per hospital. None of the respondents in Olenguruone hospital agreed that the data collection tool captured all the data for all the services offered. This was emphasized by a KII who stated that “this *tools are so many, repetitive, and only collecting what the donors or sponsors wants ,for example in our hospital we have many cases of assaults, attacks, animal products related diseases e.g. brucellosis, but none of the data collecting tools availed by the government captures that….KII(04)”* The findings for Subukia hospital on completeness of data was (71.4%) and tool validity (35.7%). Of the respondents, 71.4% of the Molo hospital health management team agreed that the hospital routine health data was accurate and 60.7% acknowledged that data management was carried out in the hospital in regard to the routine health data. Naivasha hospital performed averagely in all aspects of the data quality.

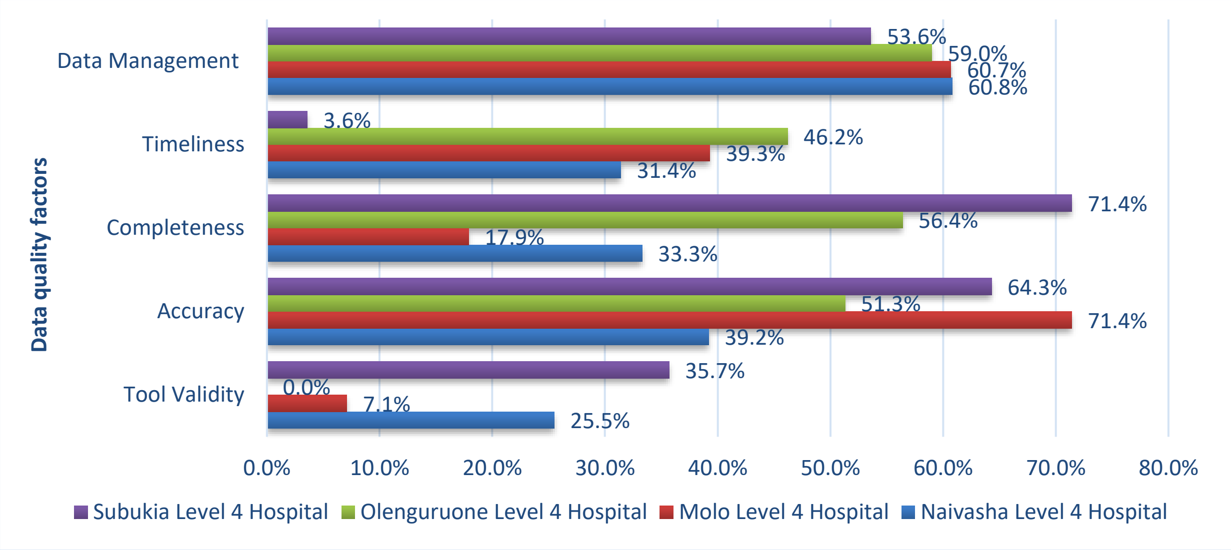

Figure 1: Dimensions of data quality factors per health facility

On average, on all data quality dimensions, Subukia hospital had an average of 45.72%, Molo had 39.28%, Olenguruone had 42.58% and Naivasha had 38.04%.

Additionally, an observation checklist (n=4) was used to identify presence or absence of list of items representing quality data and evidence of data. Figure 4.2 indicates that all health facilities had storage facilities such as cabinets or shelves or computers, evidence was also present of the state of the available filled data collection tools (completeness, accuracy, last updates, etc.).There was evidence of a departmental meeting for data review or supervisor feedback held in half in the last 3 months, patient satisfaction survey questionnaire were filled in the last 3 months, presence of data office and evidence of recorded meetings on data management. Two of the facilities had, illustration of data monitoring and analysis and health facilities had operational HMIS computer. However, in one facility it was noted that there were notable data entry errors in the tools submitted.

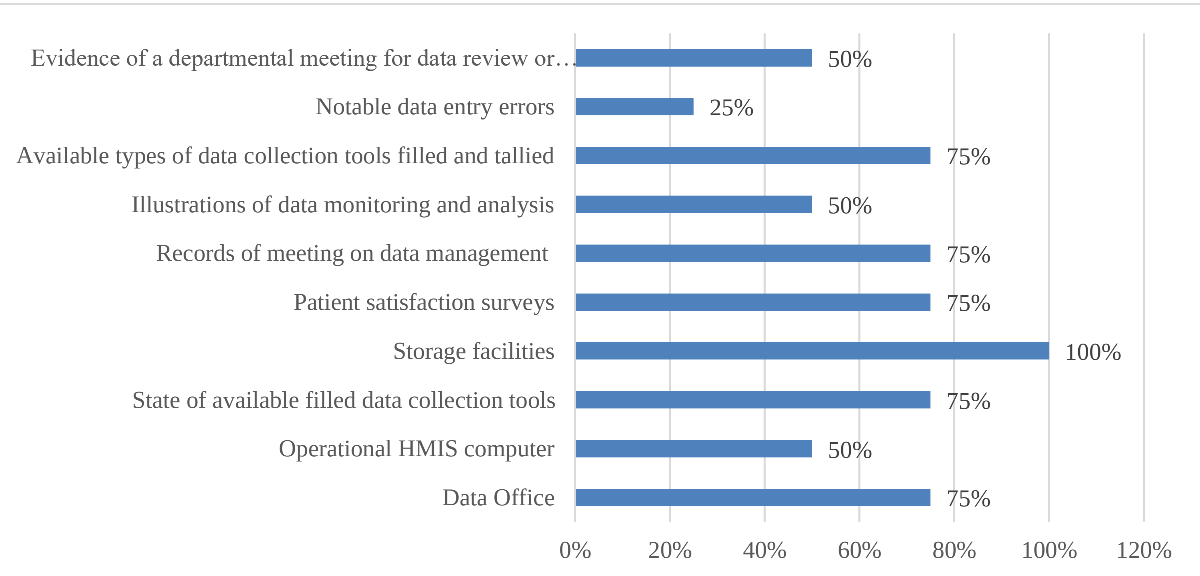

Figure 2: Evidence of quality data practices in health facilities

Routine health data use and data quality factors

In the bivariable logistic regression analysis, accuracy and data management were factors associated with good routine health data utilization at a p value of less than 0.02. The findings indicated routine health data with good accuracy was 2.9 times likely to be utilized for decision making compared with data classified as of poor accuracy. This was statistically significant at $p<0.05$. Similarly, routine health data which adhered to good data management was 1.8 times likely to be utilized for decision making than routine health data with poor data management practices and this was not statistically significant ($p=0.079$). Table 5 shows the bivariate analysis of the data quality factors with routine health data utilization.

Table 5 : Bivariate analysis Data quality factors influencing routine health data utilization

Variable	RHD utilization		Bivariate Logistic Regression	
	Poor (n)	Good (n)	COR (95% CI)	P-value
Tool Validity				
No	57	64	1	
Yes	13	12	1.216	0.656
Accuracy				
Poor	42	26	1	
Good	28	50	2.885(1.471-5.655)	0.02*
Completeness				
Poor	40	42	1	
Good	30	34	1.079(0.561-2.077)	0.819
Timeliness				
Yes	24	22	1	
No	46	54	1.281(0.636-2.578)	0.488
Data Management				
Poor	34	26	1	
Good	36	50	1.816 (0.933-3.537)	0.079*

Organizational Factors influencing RHD use

Health Facility Characteristics

There were organizational factors that influenced use of routine health data in decision making by management teams in the selected level 4 Hospitals in Nakuru County. Table 6 provides a summary of the characteristics of the sampled health facilities. Majority (54.1%; n=79) of the health facilities had been in existence for over 10 years while 45.9% (n=67) had existed for a period between 6-10 years. About 45.9% (n=67) had a bed capacity of 50 beds or less, 19.2% (n=28) reported having 51-100 beds and 34.9% (n=51) with 101-150 beds.

Table 6: Characteristics of the health facilities

Variable	Frequency (n)	Percent (%)
Years of Health Facility existence		
6-10 years	67	45.9
Above 10 years	79	54.1
Bed capacity of the facility		
1-50 beds	67	45.9
51-100 beds	28	19.2
101-150 beds	51	34.9
Services offered in the facility		
OPD	146	100
ANC	146	100
R.H	146	100
Drug Dispensing	146	100
Surgery	50	34.2
Laboratory	146	100
Inpatient	146	100
Daily patients' attendance		
26-50 patients	67	45.9
Above 50 patients	79	54.1

The HMT reported that the health facilities offered every service that information was sought apart from 34.2% (n=50) who indicated that surgery was provided in the health facility. Over half of the respondents reported that they daily attend to above 50 patients while 45.9% attended to 26 and 50 patients daily.

Data Collection

Table 7: Data collection in the health facilities

Variable	Number	Percent (%)
Data collection tools		
Registers	113	77.4
Tally Sheets	30	20.5
Summary forms	32	21.9
Computers	105	71.9
Others	11	7.5
Cadre collecting data		
Nurses	71	48.6
Clinical officers	20	13.7
Doctors	18	12.3
Health records	96	65.8
Casuals	8	5.5

Incentives

Majority of the respondents reported that the HMT received mainly training & benchmarking (71.9%, n=105) as incentives followed by 57.5% (n=84) who claimed to have received job promotion while 47.9% (n=70) were given pay rise. A KII respondent stated that "…we do try to encourage the health workers especially nurses and health records officers to capture all the services and relevant data as they go about their work, however the data captured is not comprehensive may be due to the shortage of staff on the ground visa vis the amount of work to be done. This makes it difficult to recognize those that collect and use data and also even the little motivation given is not appreciated due to fatigue and frustration at work." Figure 4.3 below shows the summary of the incentives the HMT is receive.

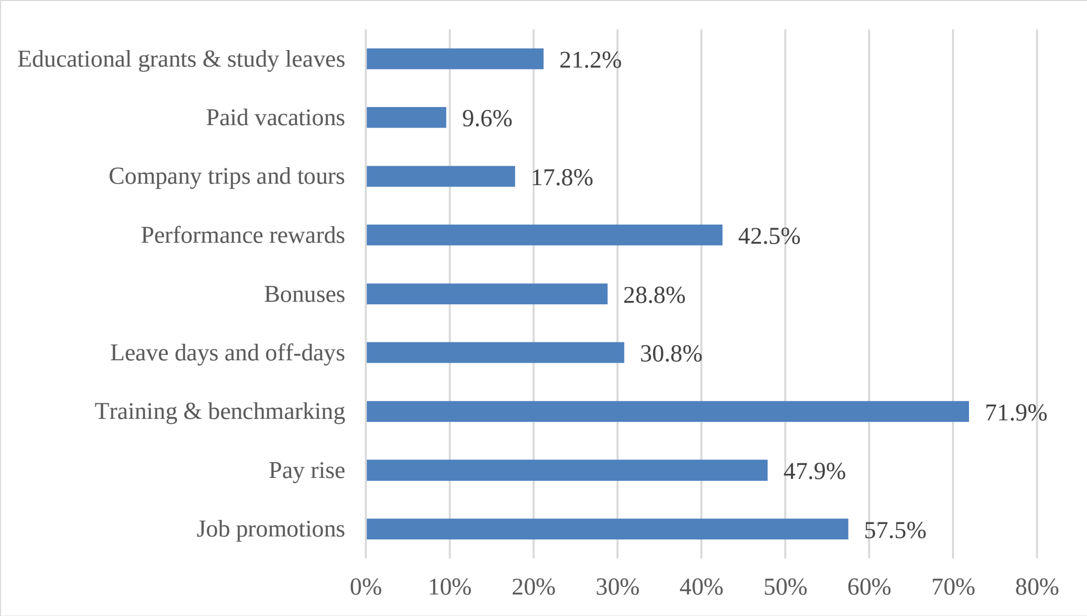

Figure 3 : Incentives received by the hospital management team

Use of modern ICT in the facility

About 86.3% (n=126) use modern information and communication technology in its operations while only 13.7% (n=20) does the converse figure 4 below.

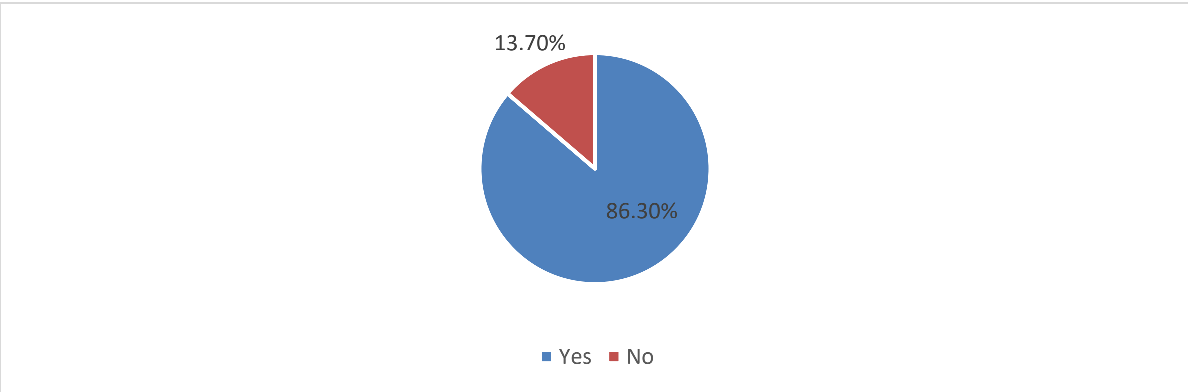

Figure 4: Use of modern technology

Leadership style

The leadership of the various hospital was reported to be dominantly democratic (59.6%, n=87) while 24.7% believed it was transformational, 9.6% argued that it was transactional and only 2.1% believed it was autocratic as indicated in figure 4.6 below.

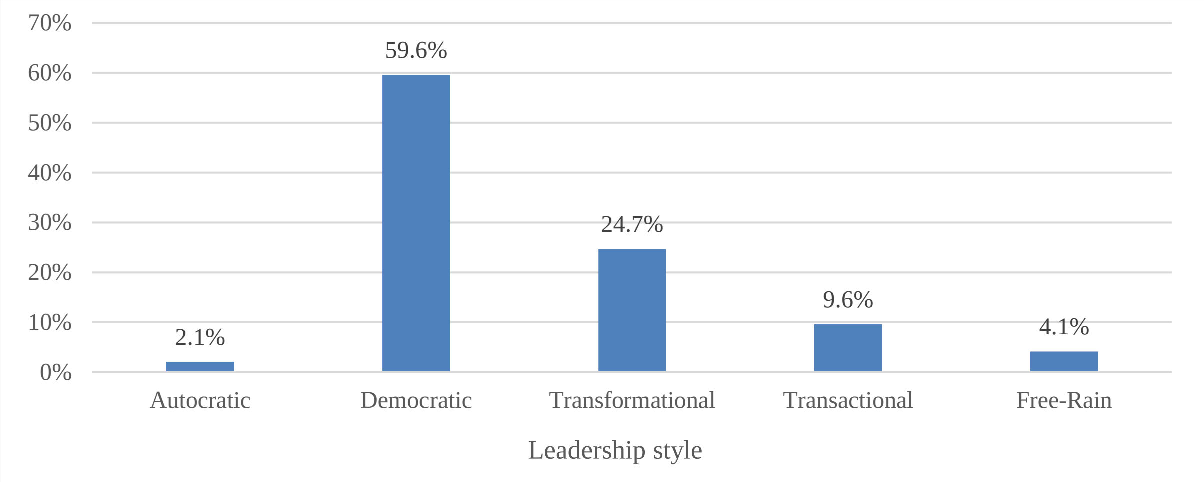

Figure 5: Leadership style

Routine health data use and Organizational factors

Table 4.9 below shows the findings of a bivariate regression analysis of organization factors and utilization of routine health data. Most of the factors such as facility years of existence was found not to be statistically significant at p<0.05.

Table 8 : Bivariate analysis of organizational factors influencing routine health data utilization

Variable	**RHD utilization**		**Bivariate Logistic Regression**	
	Poor (n)	**Good (n)**	**COR (95% CI)**	**P-value**
Facility years of existence				
6-10 years	37	30	1	
Above 10 years	33	46	1.719(0.891-3.317)	0.106
Bed capacity of the facility				
1-50 beds	37	30	1	
51-100 beds	6	22	4.522(1.626-12.58)	0.04*
101-150 beds	27	24	1.096(0.528-2.277)	0.805
Use of register				
Yes	49	64	2.064 (1.125-5.643)	0.044*
No	21	12	1	
Leadership style				
Autocratic	2	1		
Democratic	30	57	3.8(0.331-43.634)	0.284

Transformational	28	8	0.571(0.046-7.143)	0.664
Transactional	7	7	2(0.146-27.447)	0.604
Free-rain	2	3	3(0.15-59.89)	0.472
Use of modern technology				
No	12	6	1	
Yes	56	70	2.5(0.883-7.81)	0.085

As reflected in the table above, facility with a bed capacity of 51-100 beds was found to be significantly associated with good routine health information use [COR= 4.522 95% CI (1.626, 12.58)] at p-value 0.04. From the bivariate regression analysis, the type of leadership was found not to influence use of routine health data in decision making. Most leadership styles, were not statistically significant ($p>0.05$). The use of modern technology was 2.5 times likely to influence use of routine health data compared to facilities without modern technology however, this was found not to be statically significant, implying it is not an important factor in utilization of routine health data.

Demographic, data quality and organizational factors associated with utilization of routine health data

During the analysis,binary logistic regression was used to identify factors associated with the utilization of the routine health information system. The variables with a p value <0.2 were selected as candidate variables for the multivariate analysis. Finally, variables with $p<0.05$, during multivariable analysis were considered as statistically significant. To estimate the significance of association, odds ratios used to determine the strength of the association between dependent and independent variables with a 95% Confidence Interval. Both Crude Odds Ratio (COR) and Adjusted Odds Ratio (AOR) with 95% confidence interval were estimated to show the strength of associations. Hosmer–Lemeshow goodness-of-fit was done to check on the fitness of the model. The omnibus test was significant (p-value <0.0001) and Hosmer– Lemeshow's test was found to be insignificant (p-value =0.387), which indicated that the model was fitted.

Table 9: Multivariable logistic regression analysis of factors associated with utilization of routine health data

Variable	B	p-value	AOR	95% C.I AOR	
				Lower	**Upper**
Gender					
Male			1		
Female	-0.321	0.417	0.725	0.334	1.575
Age					
Below 25 years			1		
26 - 35 years	0.068	0.935	1.070	0.210	5.447

36 - 45 years	-0.136	0.862	0.873	0.188	4.059
45- 55 years	-0.396	0.625	0.673	0.137	3.300
Above 55 years	0.394	0.664	1.483	0.250	8.784
Accuracy					
Poor			1		
Good	0.861	0.025*	2.365	1.113	5.023
Data Management					
Poor			1		
Good	0.376	0.324	1.456	0.691	3.069
Facility years of existence					
6-10 years			1		
Above 10 years	0.274	0.504	1.315	0.590	2.929
Bed capacity of the facility					
1-50 beds			1		
51-100 beds	0.991	0.060	2.694	0.825	8.795
101-150 beds	0.037	0.101	1.038	0.431	2.497
Use of registers					
No			1		
Yes	0.827	0.043*	2.286	1.026	5.092
Use of modern technology					
No			1		
Yes	0.891	0.152	2.437	0.721	8.239

Table 9 shows results indicating the accuracy which was found to be significantly associated with Routine health data use [AOR= 2.365; 95% CI (1.113, 5.023)] at p-value 0.025. The respondents who agreed that the hospital collected current, accurate and adequate data were1.474 times more likely to use good routine health data for decision making than those who believed otherwise. Use of registers for data collection was found to be significantly associated with Routine health data use [AOR= 2.286; 95% CI (1.026, 5.092)] at p-value 0.043. Those who used data collected on registers were 2.286 times more likely to practice and use good routine health data than those who used other data collection tools. Majority of the factors such as gender, age, data management, facility years of existence, bed capacity and use of modern technology were found not to be statistically significant with good practice of routine health data use among health management team.

CONCLUSION AND RECOMMENDATIONS

Conclusion

The respondents were noted to be predominantly middle aged at 36-45years thus comprising of energetic workforce which is effective for management. However, majority were male in a female dominated profession.

Based on the results on the extent of data use at utilization index of 62.9%, this translated to data being often used in decision making. However, in some of the crucial managerial activities such as policy development, customer feedback surveys and fund allocation were seen to have a low data use index of averagely 55% translating to only sometimes use. This requires immediate intervention since policy helps establish guidelines that benefit patients, health care organizations as well as helps prevent human errors around medical decisions.

The major influence of routine health data use in decision making among the HMT members was explained by changes in data quality factors. Improving quality of data from the point of collection collation, analysis and dissemination of information would contribute to the increase in data demand and use and thus improve the kind of care given to our communities.

In the organizational factors, it was noted that the data collecting tool commonly used were the registers, followed by computers. The complaint by KII on proliferation of this registers, increased workload and lack of motivation was noted to be the key challenge in achieving quality data for use in decision making.

Recommendations

Based on the conclusions reached by this study, the following recommendations were made:

i. The health managers and health workers especially women should be empowered through training and motivation to access, synthesize and consume data so as to support information use for decision making and to begin integration early, the ministry of health in conjunction with the regulatory bodies of the health professionals should introduce HMIS and its application in health management in the pre-service curriculum for all health care professionals.

ii. The HMT members with support from the CHMT should develop Standard Operating Procedures that clearly states the role, value, effective data collecting tools and process of routine health data collection, storage, retrieval, use and monitoring with a view to improve data demand and use culture, quality of data and health service delivery.

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