International Research Journal of Public and Environmental Health Vol.3 (7),pp. 151-161, July 2016
Available online at http://www.journalissues.org/IRJPEH/
http://dx.doi.org/10.15739/irjpeh.16.020

ISSN 2360-8803

Original Research Article

Socio-demographic factors affecting data quality of routine health management information system (RHIS): Case of Uasin Gishu County referral hospital, Kenya

Received May 4, 2016 | Revised 15 June, 2016 | Accepted 2 July, 2016 | Published 17 July, 2016

[1]Samuel Kiprono Cheburet*
and
[2]George W. Odhiambo-Otieno

[1]Ministry of Health, Nairobi, Kenya, P. O. Box 30016-00202 Nairobi Kenya.
[2]Kenya Methodist University, Department of Health System Management, P.O. Box 45240 - 00100, Nairobi, Kenya.

*Corresponding Author Email: samuelcheburet@gmail.com

To address pressing health issues, emphasis on global health agenda have been shifted from disease-specific approaches to strengthening health systems to provide quality patient care. The success of running health management systems is highly dependent on the knowledge, skills, motivation and deployment of people responsible for organizing and delivering health services. Therefore, effectiveness and efficiency in the management of today's health systems depend on the well-being of its human resources. The existing crisis of human resource capabilities and non-alignment of existing policies to strengthen health systems is a tragedy in waiting. The study was carried out to determine how socio-demographic factors of health workers affected data quality. Cross-sectional study design was used. Data was collected using a structured questionnaire from a target population of 82 respondents. A one-way ANOVA was conducted to compare effect by the age of respondents on the quality of data with F-value of (224.51) at a p-value of 0.000 which is within the acceptable threshold value of 0.05. Finally, existing human resource policies need to be institutionalized to enhance strategic decision and policy development in improving health systems process design and implementation.

Key words: Socio-demographic, data quality, routine, health management information system.

Abbreviations :DAAD: German Academic Exchange Service, **GoK:** Government of Kenya, **HIS:** Health Information System, **HMIS:** Health Management Information System, **MoH:** Ministry of Health, **MoHSW:** Ministry of Health and Social Welfare, **RHIS**: Routine Health Information System, **GoS**: Government of Siberia, **WHO:** World Health Organisation

INTRODUCTION

The World Health Organization has identified health information systems as one of the six building blocks of a health system. These building blocks include: service delivery, health workforce, health information, medical products, vaccines, and technologies, financing and leadership and governance. The paradigm shift in addressing the pressing health issues globally from disease-specific approaches to strengthening health management systems is, to provide quality patient care. The multifaceted nature of health systems and the spread of direct and indirect responsibilities across multiple sectors, pose challenges in monitoring performance (Kihuba et al., 2014; WHO, 2007).

Emphasis is placed on the importance for institutions to discover how data quality deficiencies have a significant impact on their most strategic business initiatives, often holding them back from achieving the growth, agility and competitiveness that they desire. In addition to challenges with growth and agility, compliance and transparency pressures increasingly bring data quality issues to the forefront (Gartner, 2011).

Information is needed to track how well health systems respond to increased inputs and improved processes, and the impact they have on improved health indicators. However, on the supply side, there are major gaps in data availability and quality. It is imperative to note that the success of running a health management system is highly dependent on the knowledge, skills, motivation and deployment of the people responsible for organizing and delivering health services. Therefore, it is good to note that the effectiveness and efficiency in managing today's health systems depend on the well-being of its human resources within right norms and standards (Ledikwe et al., 2014; MoH, 2013).

Inadequate human resource coupled with other social absenteeism's which are sometimes common in the public sector in high- and low-resource settings is often not addressed in policy frameworks in health systems in order to improve the quality of information (Belita et al., 2013). Efficient use of minimum data for managing cases, clinics and community health services is essential. There is an urgent need to reform existing human resource crisis and alignment to health information systems design and implementation. Multitudes of underutilized data are still being collected at the operational level by already overburdened health workers. Later, it follows a tedious path of collation and upward transmission with little potential for analysis and uses let alone managerial value. The need to do more with less is especially important because the health sector faces ever increasing demands while receiving inadequate or decreasing resources (Odhiambo-Otieno, 2005).

The design and implementation of a health information system should be well known by the people collecting data and generating needed information by ensuring that there is proper training, recruitment, deployment and retention of technical health workers. A national strategic health workforce plan, implemented by HRH partnership and specific to the needs of the country in question, should be based on available data, operationally realistic and responsive to the health priorities. As countries continue to strengthen their human capacity whose primary intention is enhancing health, many are faced with attrition, staff wellbeing, and other social dynamics. Health workers are empowered to use the routine information they collect while, understanding the importance of good quality data for improving health outcomes (Bill and Melinda Gates Foundation, 2015).

The demand for quality data from RHMIS has increased over time due to the need for country-level progress reporting towards the attainment of the United Nations Millennium Development Goals and global health initiatives (Karuri et al., 2014; Mpofu et al., 2014). The demand is more with the advent of the current initiative of the Sustainable Development Goals (SDGs). As pointed by Measure Evaluation, (2012), global decision makers require timely and accurate information from routine health activities for the formulation of policies, resource allocation, and day-to-day management decisions. HIS Hub, (2013) noted an ever-increasing global recognition of the importance of health information systems for strengthening health systems, developing public health policy, and improving accountability and transparency. Therefore, the need for reorienting and redirecting health workers at all levels of the system to change their attitude in the way they handle data is key in achieving organizational values (Anyangwe and Mtonga, 2007; MOHSW, 2012).

The necessity for understanding the human resource at hand based on their social- demographic factors in relation to the adequately skilled and equitable distribution of human resources for health is critical. The terms of employment play a critical role in the establishment of human resource based on norms and standards. The nature of data production in the health industry is intensive and hence, the development of human resource policies should be based on empirical evidence in the work environment. The assumption made was that the personnel in-charge of the facility is trained on HMIS hence would be able to fill in most, if not all, the tables that may appear complex for those not trained in government facilities (Simba and Mwangu, 2006).

Marital status has been reported to influence absence from work in different ways in different settings where sick leave, workshop or seminar attendance, annual leave, absenteeism due to family problems, involuntary absence occurring for reasons beyond the employees' control and voluntary absence occurring when the employee makes the decision not to go to work (Belita et al., 2013; Ledikwe et al., 2014).

It is apparent that employee behaviour may influence organization-level performance given that many employees never support a positive relationship among financial performance, labour productivity and service quality at any point in time. Poor quality data is affected by inadequate policies on outputs of the health system such as availability, quality and use of health information and services; health outcomes in terms of mortality, morbidity, disability, well-being, disease outbreaks and health status and difficult in determining health inequities in coverage and use (Abouzahr and Boerma, 2005; Brown et al., 2015; Wanjau et al., 2012).

A health workforce planner requires adopting and putting in place an effective, evidence-based policy environment that is conducive to transformative development in the production of data in the organization. Investment in health workforce development, deployment and management are of necessity in the production of data. Critical information on availability and distribution of health workforce is often incomplete, inaccurate and out of date; while, few countries have systems that can monitor service delivery, data on population access to essential health services are often limited and negatively affect the overall quality of data being generated from routine health management information systems. Belita et al. (2013) show that marital status has been reported to influence absence from work in different ways and in different settings such as where sick leave, workshop or seminar attendance, annual leave, absenteeism due to family problems, involuntary absence occurring for reasons beyond the employees' control and voluntary absence occurring when the employee makes the decision not to go to work.

Ministries of Health should also put up mechanisms for distribution and staff tracking with a balance across all countries and rural-urban areas which may affect the overall loss of data being generated. Age is a vital social demographic factor which could influence the quality of data. The need for injecting energetic personnel to supplement the existing staff becomes imperative when demographic change leads to an ageing workforce which in turn affects their performance to work (Pfeifer & Wagner, 2014).

Data validation procedures and data quality assurance need to be enhanced to ensure that data is not just timely but also accurate, complete, comprehensive and relevant to realize what the system was designed for (HMN, 2008). The current HMIS is experiencing broad problems such as existence of overlapping data collection tools, different health professionals such as nurses as the majority, physicians, health records and information officers, data clerks, and other allied health professionals who have varied levels of training skills and competencies to participate in data collection, collation, analyses and information use (MoH, 2009; 2014b). There are numerous deficiencies where decisions are based on political delusions or surveys which are insensitive to change over time (Measure Evaluation, 2009).

In Kenya, employees are entitled to recognize annual leave, paternity and maternity leaves which may be factors that compromise the quality of information collected (Kenya Labour Laws, 2012). When an expectant mother is employed in one year, file for three months maternity leaves in addition to annual leave, her absence would then take half a year. Consequently, the absence of human resources may jeopardize the quality of the data in terms of completeness and timeliness.

Measure Evaluation (2010) emphasises that poor data quality limits stakeholders' ability to use data for evidence-based decision making and has a negative impact on facilities' strategic planning activities and their efforts to advocate for resources. Poor quality data was cited as the primary technical constraint limiting staff's ability to make effective decisions. Data entry backlogs also affected information use because of delayed reporting. Information users and producers perceived insufficient HMIS skills as the key individual constraint to information use, with data users expressing a need for training to improve data collection skills and analysis.

MATERIALS AND METHODS

A cross-sectional study design with the combination of quantitative and qualitative research was employed in this study. Quantitative research tools were used in collating data on the number of respondents who presented the criteria when analyzed by age, marital status and length of service while qualitative measures were employed to generate more in-depth information of the subject matter and validate the results.

In identifying the number of respondents representative of the total population, non-probability sampling, specifically purposive sampling was used to elicit data from the health facility while quantitative sampling, particularly census method was used to obtain data from every health worker participating in data processing on a daily basis. The entire health workforce from each department was assigned unique numbers due to the fact that all population collecting data were the target population (82 participants) with a response rate of 81 (98.8%) obtained.

The study used interview questionnaires whose development was guided by research questions, literature review and subjected to correction and validity. A structured questionnaire was utilized for the purpose of achieving the objectives of the study. The questionnaire, containing both closed and open-ended questions was administered to determine how socio-demographic factors such as age of respondent, sex, and marital status affect data quality of routine Health Management Information System. Based on the fact that the study population was heterogeneous, key informant interviews were carried out to obtain more in-depth information on the subject matter based on the research objectives. Key informant Interviews targeted two (2) key focal managers who were purposively selected by virtue of their positions (Facility In-charge and Information Manager) to shed light.

The independent variables for this study are; age, marital status, years of employment, type of leave while the dependent variable was the data quality of RHMIS. For the purpose of analyses, Stata and SPSS software were used where descriptive and inferential analyses were employed. Descriptive statistics such as frequencies, percentages, mean and standard deviation were employed to describe the general data for this study. To reveal any differences between selected socio-demography factor and data quality, inferential analyses using ANOVA was used while for determining relationship among selected sociodemographic factor and data quality of RHMIS. The results are presented in the tables and charts.

RESULTS AND DISCUSSIONS

General characteristics of the respondents

Among the 82 health workers who were expected to participate in the study to determine how socio-demographic factors affect data quality of RHMIS, 81 accepted, yielding a non-response rate of 1.2%. Table 1 shows the age distribution of respondents with 11 (14%) being over 50 years. Majority 76(93.6%) responded that the age of those participating in the collection, collation, and transmission of routine health data affected data quality. The mean age was 38.086, SD 7.5 with an average age of 36.4 ± 8.7 39.8 ± 7.5. The finding recognizes that changes in people demographic may also influence data quality than other factors. Among the health workers interviewed, 100% were also responsible for the daily data

Table 1. Distribution of respondents per age group (n=81)

Age group	N	Mean	Std. deviation	95% confidence Interval for mean	
				Lower bound	Upper bound
20-29	8	28.38	0.92	27.61	29.14
30-39	40	33.6	2.58	32.77	34.43
40-49	22	43.09	3.01	41.76	44.42
Above 50 years	11	51.45	1.04	50.76	52.15
Total	81	38.09	7.54	36.42	39.75
	Test of homogeneity of variances				
	Levene statistic	**df1**	**df2**	**sig.**	
Age group	7.41	3	224.51	0	

ANOVA						
		Sum of squares	**df**	**Mean square**	**F**	**Sig.**
Age group	Between groups	4076.37	3	1358.79	224.51	0
	Within groups	466.02	77	6.05		
	Total	4542.4	80			

Table 2. Distribution of respondents per age group and marital status

Age group	Marital status No (%)		
	Married	**Single**	**Total**
20-29	5 (6)	3 (4)	8 (10)
30-39	37 (46)	3 (4)	40 (49)
40-49	22 (27)	0 (0)	22(27)
50 and above	11 (14)	0 (0)	11(14)
Total	75 (93)	6 (0)	81 (100)

generation of RHMIS activities. The results also were supported by key informant 01 thus:

“*The experience of health workers on various disciplines in relation to the frequency of working does not translate to improved data quality but stuck to old approaches of addressing data quality*”.

Participants perceived age as a socio-demographic factor which has an effect on data quality of RHMIS. The variation was significant at p=0.000. The result also showed significant results based on the test of homogeneity of variance with a p-value of 0.000. This was within the acceptable threshold value of 0.05. Also one-way ANOVA was conducted to compare the effect of age of respondents on the quality of data with F-value (224.51) at a p-value of 0.000 and was within the acceptable threshold value of 0.05.

The findings implied that 40% of the employees were above 40 years old. The study showed that after increasing the mandatory retirement age from 55 to 60 years, governments had a large number of aged workforce which affects performance (MoH, 2014). The age of human resource is a cornerstone which influences overall data quality design and implementation process. Moreover, the government of Kenya has made some strive in the development of institutional documents which act as an advocacy tool for authorities in the deployment of human resource based on norms and standards to achieve universal health coverage and well-distributed age bracket to allow succession management from the new generation to the next (MoH, 2014a). However, the same argument that age is rarely an employment requirement and a poor predictor of job performance which may have an important implication in enhancing service delivery performance and quality of data.

Table 2 shows that over ninety percent (75) of the respondents were married while 6 (7%) were single. Slightly over one-third (37) of the married participants were within the age bracket of 30-39 years. Marital status proved to have a significant positive weak association with data quality (p = <0.05, r=0.004). This indicated that gender can be applied as one of the factor that may affect data quality. One of the key informants showed that:

“*marital status played a key role on data quality and the result indicated a positive result by indicating that most married civil servants gave priorities on social matters. For instance, where one had to be absent from work which created backlog where a shortage of staff was a reality.*

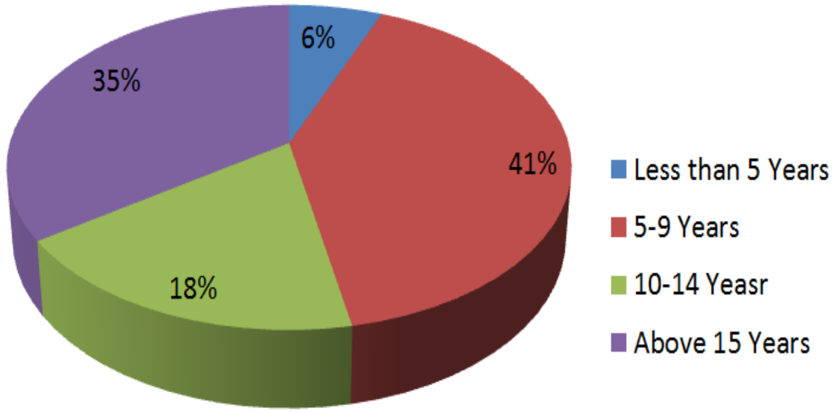

Figure 1: Number of years in the current station

Moreover, the majority of the staff had put more weight on follow- up of social matters other than performing their official tasks. However, single staff preferred to work for more hours due to minimal social matters." "*Therefore, priorities and commitments differed for married and single individuals. Those who live close to the workplace with their family had less issues on commitments towards work than those leaving outside the respective administrative units".*

The key informant further provides an example thus:

*"...during devolution, many of the newly employed staff were having difficulty transferring from one county to another except in the case of cross transfers."(*Key informant, 001).

These affected the productivity of staff and equally, the eventual data quality is affected due to a shortage of staff. In this case, these will result in pending work in terms of collection, collation, analysis and reporting" (key Informant, 001). This agrees with results by Belita et al. (2013) who showed that marital status was viewed to influence work performance. For example, when one had to be absent from work in different ways and settings such as sick leave, workshop or seminar attendance, annual leave, absenteeism giving reasons in dealing with family problems, involuntary absence occurring for reasons beyond the employees' control and voluntary absence occurring when the employee makes the decision not to go to work (Belita et al., 2013; Ledikwe et al., 2014).

Figure 2 shows the number of years the respondents stayed at the current health facility (n=81). Less than ten-5(6%) -of the respondents had worked in their current station for less than 5 years, 33 (41%) for a period of 5-9 years, 15(18%) for 10-14 years and 28 (35%) had experience of more than 15 years in the current health facility. This result recognises that there was staff turnover which could affect institutional recollection and in turn affect data quality of routine HMIS implementation. (Table 3).

Type of leave of the respondent

Kenyan Labour Laws (2012) entitles employees to rightfully enjoy 30 working days leave of absence for annual leave, 14 work days off for paternity leave and 120 days off for maternity leave. Table 4 below, Appendix 1 shows the type of leave among respondents. Majority 81(100%) of the respondents had reported having enjoyed this right. The result also agrees with Belita et al. (2013) who demonstrated that marital status has been reported to influence data quality based on absence from work in different settings such as sick leave, workshop or seminar attendance, annual leave, absenteeism in dealing with family problems, involuntary absence occurring for reasons beyond the employees' control and voluntary absence occurring when the employee makes the decision not to go to work (Belita et al., 2013). Moreover, most countries have labour laws where civil servants have the right to vacation and leave in accordance with general labour legislation and the special collective contract. A civil servant has the right to annual vacation for a minimum of 20 and maximum 30 days according to criteria determined by special collective contract (GoK, 2012; SoB, 2008).

These results have a bearing on the state of data quality of RHMIS and its implication on the processes of RHMIS where the level of staffing in terms of numbers and prevailing policies.

It was also emphasised that a civil servant has the right to annual vacation for a minimum of 20 and maximum 30 days according to criteria determined by special collective contract (GoK, 2012; SoB, 2008). All females have a right to three months maternity leave in addition to annual leave, this means that one staff can end up spending closer to a half a year before resuming work. The existing policies, therefore, is not in line with day to day operations where an acute shortage of critical staff in terms of numbers and skills are absent. As pointed by Measure Evaluation, (2012) global decision makers require timely and accurate information from routine health activities for the

Table 3. Crosstab on the cadre and teams of employment of the respondents

Profession	Contract	Permanent and pensionable	Total
	Frequency (%)		
Clinical officer	1(1)	4(5)	5(6)
Data clerk	1(1)	1(1)	2(2)
Health Information officer	1(1)	2(2)	3(4)
Medical Lab technician	0(0)	1(1)	1(1)
Medical Lab technologist	0(0)	1(1)	1(1)
Nursing	13(16)	42(52)	55(68)
Nutritionist	0(0)	4(5)	4(5)
Ophthalmologist	0(0)	2(2)	2(2)
Pharmacist	0(0)	2(2)	2(2)
Physiotherapist	0(0)	1(1)	1(1)
Psychology	0(0)	1(1)	1(1)
Public health	0(0)	3(4)	3(4)
VCT counsellor	0(0)	1(1)	1(1)
Total	16(20)	65(80)	81(100)

Table 4. Type of leave and working days of the respondents

Type of leave	Female	Male	Total
	Frequency (%)		
Annual Leave	51 (63)	26 (32)	77 (95)
Maternity leave	24 (30)	0 (0)	24 (30)
Paternity Leave	0 (0)	12 (15)	12 (15)

formulation of policies, resource allocation, and day-to-day management decisions. Odhiambo-Otieno (2005) in his study also pointed out that urgent need to reform existing human resource and alignment to health information systems design and implementation is critical for the success of good quality information. It is noted that multitudes of underutilized data are still being collected at the operational level by already overburdened health workers. Later, it follows a tedious path of collation and upward transmission with little potential for analysis and use, let alone managerial value. Emphasis is needed to do more with less especially during data collection as the health sector faces ever increasing demands while receiving inadequate or decreasing resources. One of the key informants also pointed out that:

"*being on permanent, temporary or casual will affect how you handle your work. At times staffs are not promoted, re-designated or supported on career progression and with minimal recognition of health records personnel which brings demotivation. Those on contract can be terminated anytime without notice and this affects coverage of work where there is a shortage of staff*" (Key Informant, 002).

However, HIS Hub (2013) also pointed out an ever-increasing global recognition of the importance of health information systems for strengthening health systems, developing public health policy and improving accountability and transparency. In order to strengthen data quality at all levels, we therefore need reorientation and redirecting of health workers at all levels of the system to change their attitudes in the way they handle data in achieving organizational values (Anyangwe and Mtonga, 2007; MOHSW, 2012). Consequently, this result demonstrates the impact of policies in negatively influencing the production of data in the health industry which has also led to poor data quality. Kenya labour laws (2012) recognizes that every employee is entitled to annual leave, paternity, study leave and maternity leave which does not commensurate with the availability of human resource to cover during absence leading to backlog of data collection, transformation and dissemination for use (Laws, 2012).

Table 5 Appendix 2 shows the results from respondents that were asked if they had ever gone for any leave in the year 2014 and what the duration was. All the respondents reported having gone for entitled leave with 55 (68%) of them females and 26 (32%) male respondents. One-quarter, (20) of the respondents had more than 60 working days before resuming work, 49 (60%) had less than 30 working days. On the other hand, if one combines maternity and annual leave days, it is approximately more than 90

Table 5. Type of leave and working days of the respondents

Leave days	Female	Male	Total
	Frequency (%)		
Less than 30 working Days	33 (41)	16 (20)	49 (60)
30-60 Working Days	2 (2)	10 (12)	12 (15)
Above 60 Working Days	20 (25)	0(0)	20 (25)
Total	55 (68)	26 (32)	81 (100)

Table 6. Delegation of work by the respondent and pending work

Officer delegated work to cover	Pending work		
	No	Yes	Total
No	2 (2)	11 (14)	13 (16)
Yes	18 (22)	50 (62)	68 (84)
Total	20 (25)	61 (75)	(100)

working days excluding weekends. The existing policies do not look on the workload and coverage an individual does before proceeding for leave. One of the key informant interviewees indicated that “

Kenyan government provides a right for officers to leave every financial year (between July to June of the following year)". One can either go for annual, maternity, paternity, sick or study leave and in areas where there is one or few staff, will lead to late collation and reporting of data. Take for example a staff going for maternity leave for 90 days plus annual leave for 30 days which brings to a total of 120 days. This means that the data availability will not be there for more than 4 consecutive months, (Key informant, 002).

The findings also demonstrate how existing policies implemented in various countries with other labour laws for civil servants which provides the right to vacation and leave in accordance with general labour legislation and how special collective contract has affected data quality. It is also illustrated that a civil servant has the right to annual vacation for a minimum of 20 and maximum 30 days according to the criteria determined by special collective contracts (GoK, 2012; SoB, 2008). The repercussion of this result will touch on the business process factors, and calls for adequate staff at all times. Emphasis is placed on the importance for institutions to discover data quality deficiencies with a significant impact on their most strategic business initiatives that often prevent them from achieving the growth, agility, and competitiveness that they desire. In addition to challenges with growth and agility, compliance and transparency pressures increasingly bring data quality issues to the forefront (Gartner, 2011). Also, poor quality data affects policies on outputs of the health system such as availability, quality, and use of health information and services; health outcomes in terms of mortality, morbidity, disability, well-being, disease outbreaks and health status and difficulty in determining health inequities in coverage and use (Wanju et al., 2012).

Table 6 appendix 3 above shows the consequence of delegation of work and pending works after proceeding on entitled leave. Majority 64(84%) delegated work while 13(16%) of the respondents did not delegate. Among those who delegated their work, slightly more than half (50) reported to have found pending work after resuming work from leave while 18 (22%) of the respondents found none. This agrees with Measure Evaluation (2010) which shows that poor data quality limits the ability to use data for evidence-based decision making and has a negative impact on facilities' strategic planning activities and their efforts to advocate for resources. Data entry backlogs or pending work affected data generation of information for use due to delayed reporting and availability of clear internal management process of staff based on skills to enhance timely data collection, analysis, and use. Moreover, Simba and Mwangu (2006) found out that the assumption was that when those in charge of the facility are trained on HMIS, health staff would be able to fill-in most, if not all of the tables that may appear complex for those not trained. Whereas in government facilities, the accountability of health facility workers in ensuring data is collected, transformed and disseminated to those interested is compromised. This was also supported from one of the key informants thus:

“*we delegate casuals to cover areas we cover as we have social, workshops or school-based classes which are self-sponsored resulting in pending work at the workplace*” (Key Informant, 001).

The consequence of these results applies to the adequacy of human resource which ends up with data quality in term of accuracy, completeness, relevance and timeliness.

RECOMMENDATION

The health industry is a data-intensive amphitheatre which needs high-quality data to support health interventions, decision-making and assure communities health. Data-use and -process have not been given adequate attention, although they are equally important factors which determine the quality of data. Based on the enactment of government policies, findings revealed that the policies do not naturally flow from planning to implementation as assumed. The study, therefore, recommends that the government should proactively closely follow-up on any policies designed aiming at paradigm shift to monitor its implementation and impact on a business process like data quality improvement. In order to strengthen the data quality of routine HMIS activities at all levels of healthcare, the national and county governments and the Ministry of Health in Kenya should increase the adequacy of human resources in terms of numbers and skills mix to support business processes.

The objectives of the study are clear and successfully accomplished. However, the study was limited to literature related to the study area but, further studies are recommended to unearth more organizational policies that could be affecting the implementation of data quality improvement process. Further research is also needed to assess the effectiveness of similar interventions on a large scale, estimate their implications and illuminate the connection between value-added data quality and better health service delivery to the general public in the global era of measurement and accountability.

ACKNOWLEDGEMENT

Sincere appreciation to my research advisor, Professor George W. Odhiambo-Otieno for the overwhelming support and inspiration accorded me to undertake this study. More appreciations go to the German Academic Exchange Service (DAAD) and Federal Ministry of Education and Research for their financial support. Lecturers, Coordinators and University management of Hochschule Neu-Ulm-Germany, University of Western Cape- South Africa and Kenya Methodist University are hereby acknowledged. The participants (health workers) in Uasin Gishu County Hospital are thus acknowledged for their invaluable time and support.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of the paper

REFERENCES

Abouzahr C, Boerma T (2005). Health information systems : the foundations of public health.

Anyangwe SCE, Mtonga C (2007). Inequities in the Global Health Workforce : The Greatest Impediment to Health in Sub-Saharan Africa. Int. J. Environ. Res. Public Health, 4(2):93–100.

Belita A, Mbindyo P, English M (2013). Absenteeism amongst health workers--developing a typology to support empiric work in low-income countries and characterizing reported associations. Human Resources for Health, 11(1)34.

Bill and Melinda Gates Foundation (2015). Operations Research on Improving Paper-based Information Systems for Child Healt.

Brown S, Gray D, Mchardy J, Taylor K (2015). Employee trust and workplace performance. J. Econ. Behavior and Organization

Gartner (2011). Measuring the Business Value of Data Quality: The Gartner Business Value Model: A Framework for Measuring Business Performance.

GoK. Kenya Employment Act (2012).

HIS Hub (2013). Prioritising data sources to strengthen health information systems in the Asia-Pacific region. The University of Queensland.

HMN (2008). Framework and Standards for Country Health Information Systems (Vol. 2nd Editio). Geneva.

Karuri J, Waiganjo P, Orwa D, Manya A (2014). DHIS2: The Tool to Improve Health Data Demand and Use in Kenya. J. Health Informatics in Developing Countries, 8(1):38–60.

Kihuba E, Gathara D, Mwinga S, Mulaku M, Kosgei R, Mogoa W, English M (2014). Assessing the ability of health information systems in hospitals to support evidence-informed decisions in Kenya (Vol. 1).

Ledikwe JH, GrignonJ, Lebelonyane R, Ludick S, Matshediso E, Sento B W, Semo B (2014). Improving the quality of health information: a qualitative assessment of data management and reporting systems in Botswana. Health Research Policy and Systems / BioMed Central, 12, 7.

MEASURE Evaluation (2009). Measuring the Impact of Health Systems Strengthening: A Review of the Literature Measuring the Impact of Health Systems Strengthening.

MEASURE Evaluation (2010). A Review of Constraints to Using Data for Decision Making Recommendations to Inform the Design of Interventions.

MEASURE Evaluation (2012). How can routine health information systems improve health systems functioning in low and middle-income countries? assessing the evidence base. Advances in Health Care Management.

MoH (2009). Health Sector Health Information System Policy. Nairobi , Kenya.

MoH (2013). Human resources for health Result: Policy Brief.

MoH (2014a). Human Resources For Health Norms and Standards Guidelines For The Health Sector.

MoH (2014b). Kenya Health Information System Annual Statistical Report 2013. Nairobi , Kenya.

MOHSW (2012). Performance of Routine Health Information System Management in Liberia :

Mpofu M, Semo B, Grignon J, Lebelonyane R, Ludick S, Matshediso E, Ledikwe, JH (2014). Strengthening monitoring and evaluation (M&E) and building sustainable health information systems in resource limited countries: lessons learned from an M&E task-shifting initiative in Botswana. BMC Public Health, 14(1)1032.

Odhiambo-Otieno GW (2005). Evaluation of existing District Health Management Information Systems: A case study of the District Health Systems in Kenya. Int. J. Med. Informatics, 74:733–744.

Pfeifer C, Wagner J (2014). Age and gender effects on workforce composition on productivity and profits: Evidence from a new type of data for German enterprises. In Contemporary Economics 8:25–46.

Simba DO, Mwangu MA (2006). Factors influencing quality of Health Management Information System (HMIS) data the case of Kinondoni district in Dar es Salaam region, Tanzania. East African Journal of Public Heath, 3(1): 28–31.

SoB. The Republic of Serbia Law on civil servants (2008).

Wanjau DKN, Muiruri BW, Ayodo E (2012). Factors Affecting Provision of Service Quality in the Public Health Sector : A Case of Kenyatta National Hospital. International Journal of Humanities and Social Science, 2(13):114–125.

WHO (2007). Everybody's Business: Strengthening Health systems to improve Health outcomes WHO's Framework for Action.

Appendix 1

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
Type_Leave_Annual_Leave	Less than 30 working Days	49	1.04	.20	.03	.98	1.10	1	2
	30-60 Working Days	12	1.17	.39	.11	.92	1.41	1	2
	Above 60 Working Days	20	1.00	.00	.00	1.00	1.00	1	1
	Total	81	1.05	.22	.02	1.00	1.10	1	2
Type_Leave_Maternity_leave	Less than 30 working Days	49	1.96	.20	.03	1.90	2.02	1	2
	30-60 Working Days	12	1.83	.39	.11	1.59	2.08	1	2
	Above 60 Working Days	20	1.00	.00	.00	1.00	1.00	1	1
	Total	81	1.70	.46	.05	1.60	1.81	1	2
Type_Leave_Poternity_Leave	Less than 30 working Days	49	1.96	.20	.03	1.90	2.02	1	2
	30-60 Working Days	12	1.17	.39	.11	.92	1.41	1	2
	Above 60 Working Days	20	2.00	.00	.00	2.00	2.00	2	2
	Total	81	1.85	.36	.04	1.77	1.93	1	2

Total of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
Type_Leave_Annual_Leave	9.78	2	78	.000
Type_Leave_Maternity_Leave	9.78	2	78	.000
Type_Leave_Poternity_Leave	9.78	2	78	.000

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Type_Leave_Annual_Leave	Between Groups	.22	2	.11	2.37	.101
	Within Groups	3.59	78	.05		
	Total	3.81	80			
Type_Leave_Maternity_Leave	Between Groups	13.30	2	6.65	144.73	.000
	Within Groups	3.59	78	.05		
	Total	16.89	80			
Type_Leave_Paternity_Leave	Between Groups	6.64	2	3.32	72.20	000
	Within Groups	3.59	78	.05		
	Total	10.22	80			

Appendix 2

Chi-Square Tests

	Value	df	Asyp. Sig. (2-sided)
Pearson Chi-Square	23.914[a]	2	.000
Likelihood Ratio	28.954	2	.000
Linear-by-Linear Association	3.461	1	.063
McNemar-Bowker Test			b
N of Valid Cases	81		

a.1 cells (16.7%) have expected count less than 5. The minimum expected count is 3.85
b.Computed only for PxP table, where P must be greater than 1.

Appendix 3

Descriptives

Pending_Work

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Yes	68	1.26	.444	.054	1.16	1.37	1	2
No	13	1.15	.376	.104	.93	1.38	1	2
Total	81	1.25	.434	.048	1.15	1.34	1	2

Test of Homogeneity of Variances

Pending_Work

Levene Statistic	df1	df2	Sig.
3.829	1	79	.054

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups (Combined)	.134	1	.134	.710	.402
Linear Term Unweighted	.134	1	.134	.710	.402
Weighted	.134	1	.134	.710	.402
Within Groups	14.928	78	.189		
Total	15.062	80			