Individual capacities influencing uses of routine health data for decision making among health workers at Muhimbili National Hospital; Dar es Salaam – Tanzania: a quantitative study.

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Abstract

Background: The availability of health workers with capacity to read and understand statistical data and then use them for work-related decision-making, therefore, supporting their institutions or the existing health system at large in developing countries is important. However, in some countries, Tanzania inclusive, this has remained critical. This requires the capacity-building of potential users. The study aimed to assess individual capacities influencing uses of routine health data for decision making among Emergency Medicine health workers at Muhimbili National Hospital (MNH).

Methods: The study design used was a descriptive cross-sectional using a quantitative approach. Stratified random sampling was used to sample Nurses, Medical officers, Residents, and Emergency medicine specialists. A semi-structured questionnaire was used to collect data. The study involved 76 health workers working in the Emergency Medicine Department (EMD) at MNH.

Results: Results showed 61.6% use of routine health data for decision making. Working experience, job title, and education level had a statistically significant association with information used for decision making. There was a statistically significant difference in routine data use between those who had poor and good knowledge to collect, analyze, interpret, and use data. Also, results showed that there was a statistically significant difference in routine data use between those who had poor and good skills to collect, analyze, interpret, and use data. Specialists had good level of knowledge and skills on data use compared to other health workers.

Conclusion: The study demonstrates partial use of routine health data for decision making with an interplay of individual capacities. A framework for statistical capacity building in Tanzania need to be built, by training a cadre of health workers with core competencies and skills in measuring progress in the health system that could generate a sustainable demand for data use within the health systems of the country.

Keywords: Health Management Information system, Capacity building, Data, Decision making, Health workers

Introduction

The fate of economic improvement is upset by a wide scope of health problems in low and middle-income countries (LMICs). Resolving these issues lays on effectively recognizing the size of problems and conveying the right solution. Nonetheless, the capacity to measure health in LMICs is undermined by low quality data, data irregularity/inconsistence, and absence of abilities to utilize existing data to educate on global health ventures (Amoah, 2018).

Significant human and financial resources have been invested worldwide in the collection of data on populations, facilities, and communities. Unfortunately, this information is often not used by key stakeholders for decision making. The failure to consider all the empirical evidence before making decisions hinders the health system's ability to respond to priority needs throughout its many levels (Measure Evaluation, 2018a). Health care providers especially in developing countries equate

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information systems as endless filling of registers, collating the data while doing minimal data analysis and reporting them to the management on a weekly or monthly basis without receiving adequate feedback (Kagoya & Kibuule, 2018). As a result, management cannot make an informed decision since data lacks quality (Lippeveld et al., 2000).

The availability of trained staff with analytical, numerical, and statistical skills is critical. Developing capacity of health workers in data use is essential. Having appropriately trained workers with the skills to implement the data-processing continuum is important to support the analysis that reflects the reality within health systems, estimates the effectiveness of policies, informs new policies and health programming and tracks progress on goals (Amoah, 2018).

Health workers have to be enhanced with sense of data ownership, and understand that their role does not end just after collecting them and transmitting to the next level (Mboro, 2017). The ultimate goal is using the data to improve health services delivery and outcomes through evidence based planning and decision making (Mavimbe et al., 2005).

Health Management Information system (HMIS) is a cornerstone for informed decision making. The system ensures that data collected from health facilities meet the quality (World Health Organization, 2008). For over 15 years, the United Republic of Tanzania has zeroed in on planning and conveying a powerful routine HMIS to facilitate local decision making to each level of health sector, and ensure timely and accurate supply of information (Nsaghurwe et al., 2021). The system is made up of various registers, tally sheets and a data entry book. Also, it includes 12 "books" of forms, registers, and reports that health workers use to report all types of diseases and health services (Mghamba et al., 2008). To facilitate data access and stimulate usage, the Ministry of Health, Community Development, Gender, Elderly and Children (MOHCDGEC) made a strategic investment in a District Health Information System (DHIS2) (Mboera et al., 2021). MOHCDGEC completed the national rollout of the system in 2013 (Measure Evaluation, 2018c). The system collect, validate, analyse, and present aggregated statistical data tailored to integrated health information management activities (Mboera et al., 2021).

There is large quantity of data being generated within Tanzania health system from public and private sectors (Somi et al., 2017). In HMIS, the ultimate purpose of collecting and analyzing data is to improve programs by enabling more informed decisions; evidence-based decisions (Measure Evaluation, 2011). To meet this purpose, the capacity of health workers need to be built as it is a process, which enables individuals, organizations and systems to improve their abilities to attain objectives and maintain ownership of the process (Amoah, 2018).

Capacity-building in statistics has not met this working definition. Capacity-building in the health workforce often focuses on producing a clinical or health-service provision workforce, with an emphasis on reducing disease incidence and prevalence, or improving health outcomes. This limited health workforce, who is not formally, trained in statistical work, research or monitoring and evaluation, stopgaps the statistical human resource in the health system, in addition to their clinical duties (Amoah, 2018). The global health and development community has broadly recognized the imperative job that capacity building plays in fortifying health systems, especially when sustainability and country ownership are a need (Measure Evaluation, 2018b).

Although a significant amount of research has been done studying routine health data use, there is still little information on the extent of implementation of capacity building strategy on improving data use for decision making among health workers. This information is needed to comprehensively improve data-informed decision-making in the health sector in Tanzania.
This study therefore sought to assess theassess individual capacities influencing routine health data use for decision making among Emergency Medicine health workers at Muhimbili National Hospital.

Materials and methods

Study Design

A descriptive cross-sectional study employing a quantitative approach was used to assess individual capacities influencing routine health data use for decision making among Emergency Medicine health workers at Muhimbili National Hospital.

Study Setting

The study was conducted at Muhimbili National Hospital, Dar es Salaam (MNH). MNH is a National referral hospital and University teaching hospital with 1500 beds, admitting 1000 to 1200 inpatients in a week and 1000 to 1200 outpatients in a week. MNH has a total of 2700 staff, among them, doctors and specialists are 300, nurses are 900, and the remaining supporting operation employees (MNH, 2019).The emergency medicine department (EMD) is one of the 13 departments in the directorate of medical services. The EMD has the main unit with triage, treatment and resuscitation areas, Mass casualty area, and an Emergency Operating Theatre. The main unit has a total of 70 nurses, 18 Registrars, 18 Residents, 8 Emergency medicine specialists, 1 Super specialist, and 28 Health Attendants. The Emergency Operating Theatre has 8 Nurses and 8 Health Attendants with specialist anesthesiologists and surgeons rotating from the MNH departments.

Sampling approach

The human resource database was used to provide a list of health workers in the EMD as a sampling frame. Stratified random sampling was used to ensure homogeneity in each stratum that is, members from each cadre are of the same characteristics. Participants were categorized into five groups, Nurses, Medical officers, residents, and Emergency medicine specialists.

Data collection

A semi-structured questionnaire was used to collect the data. The study collected data on socio-demographic characteristics of the health workers, areas of data use, and individual capacities to use data (level of knowledge and skills). The study involved 76 health workers in the Emergency medicine department at MNH who are in regular contact with clients on delivering services; who have been participating in the collection of routine health data and involved in decision making. They were stratified as follows; 55 Nurses, 11 Medical officers, 5 Residents, and 5 Emergency medicine specialists

Data analysis

Data cleaning was done to identify if there is a double entry, outliers, incorrect entry, and missing data to ensure data entered are clean before actual analysis. Descriptive analysis was done by using IBM SPSS Statistics for Windows, version 23. P-value of 0.05 for 95% Confidence Interval (CI) was used. Fisher's exact test was used to determine the significant association between socio-demographic characteristics and the dependent variable. A Kruskal-Wallis H test ("Kruskal-Wallis Test," 2008) was used to determine significance difference between independent and dependent variables.

Results

Socio-demographic characteristics

The study involved 76 health workers working in the department of emergency medicine. Out of all 76 respondents, 55 (72.4%) were nurses. Majority 50 (65.8%) of the respondents had a degree as their highest attained education level followed by 14 (8.4%) who had a diploma. Regarding work experience, 51 (67.1%) had worked for one to five years since first graduated. Out of 76 respondents who were interviewed only 8 (10.5%) were involved in supervisions (table 1).

Table 1: Socio-demographic characteristics

Variable	Frequency (n)	Percent (%)
Working duration (years)		
1 – 5	51	67.1

6-10	13	17.1
11-15	11	14.5
16-20	1	1.3
Job title		
Medical officer	11	14.5
Nurse	55	72.4
Resident	5	6.6
Specialist	5	6.6
Education level		
Diploma	14	18.4
Higher diploma	7	9.2
Degree	50	65.8
Masters	5	6.6
Supervision		
Yes	8	10.5
No	68	89.5

Use of routine health data
The overall level of RHI use for decision making

The use of routine health data was assessed using information use index (mean) established from a set of four areas of information use (table 2). In the study respondents self-rated the extent to which they use routine health data for decision making in each of the four areas in a scale of 1 to 5 with a rating score of 0% to 100% where 1 meant very low with a rating score of (0 – 20)%, 2 meant low with a rating score of (21 – 40)%, 3 meant 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 analysis results shown in table 2, routine health data for budget preparation had a mean 3.46 (69.2%), staffing decisions3.39 (67.8%) medical supply2.79 (55.8%), and planning clinical services had a mean of 2.68 (53.6%). The overall data use index was calculated by taking the mean of all four dimensions which come to 61.6%.

Table 2: Overall use of routine health data for decision making

Use area	Mean (n=76)	Rating score (%)
Budget preparation	3.46	69.2
Staffing decisions	3.39	67.8
Medical supply	2.79	55.8
Planning clinical services	2.68	53.6
Data use index	**3.08**	**61.6**

Further analysis was done using Fisher's exact test (FET) to determine if there is a significant association between respondents' general characteristics and use of routine health data for decision making. Fisher's exact test in table 3 shows a statistically significant association between a working experience (years) and level of data use for decision making (FET=21.096, p=0.035). The job title showed statistical significance with data use (FET=83.552, p=0.000). Also, education level showed a statistically significant association with data use (FET=21.052, p=0.013). Supervision had a marginal statistical association to use of routine health data for decision making, p>0.05.

Table 3: Association between Socio-demographic characteristics and level of data use

Socio-demographic characteristics	Very poor n (%)	Poor n (%)	Average n (%)	Good n (%)	Excellent n (%)	FET, p
Working experience (years)						
1-5	1(2.0)	3(5.9)	12(23.5)	32(62.7)	3(5.9)	FET=21.096
6-10	0(0.0)	0(0.0)	0(0.0)	13(100.0)	0(0.0)	
11-15	0(0.0)	0(0.0)	0(0.0)	11(100.0)	0(0.0)	p=0.035*
16-20	1(100.0)	0(0.0)	0(0.0)	0(0.0)	0(0.0)	
Job title						
Medical officer	0(0.0)	0(0.0)	10(90.9)	0(0.0)	1(9.1)	FET=83.552 p=0.000*
Nurse	1(1.8)	0(0.0)	0(0.0)	54(98.2)	0(0.0)	
Resident	1(20.0)	2(40.0)	1(20.0)	1(20.0)	0(0.0)	
Specialist	0(0.0)	1(20.0)	1(20.0)	1(20.0)	2(40.0)	
Education level						
Diploma	1(7.1)	0(0.0)	0(0.0)	13(92.9)	0(0.0)	FET =21.052
Higher diploma	0(0.0)	0(0.0)	0(0.0)	7(100.0)	0(0.0)	π=0.013*
Degree	1(2.0)	2(4.0)	11(22.0)	35(70.0)	1(2.0)	
Masters	0(0.0)	1(20.0)	1(20.0)	1(20.0)	2(40.0)	
Supervision						
Yes	0(0.0)	0(0.0)	0(0.0)	7(77.8)	2(22.2)	FET =7.261
No	2(3.0)	3(4.5)	12(17.9)	49(73.1)	1(1.5)	π=0.086

*Significant result

Individual capacities influencing routine data use
Level of knowledge

A Kruskal-Wallis H test showed that there was a statistically significant difference in routine data use between those who have poor knowledge and good knowledge in data collection, H= 6.409 (1) p=0.011, with a mean rank routine data use score of 44.98 for poor knowledge and 34.72 for good knowledge. For the case of knowledge on data analysis, results showed statistical significance difference in routine data use between those who have poor knowledge and good knowledge in data analysis, H= 5.937 (1) p=0.015, with a mean rank routine data use score of 43.39 for poor knowledge and 33.86 for good knowledge. Significance difference in routine data use was also revealed in knowledge on data presentation, H= 4.966 (1) p=0.026, with a routine data use score of 41.73 for poor and 32.63 for good knowledge. Knowledge of data use had a significant difference in routine data use, H= 10.197 (1) p=0.001 between those with poor knowledge and good knowledge. The mean rank routine data use score for poor knowledge was 42.11 and 27.68 for good knowledge. Specialists appeared to have good knowledge on data use compared to other categories, whereas out of five specialists three had good level of knowledge.

Table 4: Statistics of data use versus the level of knowledge

Knowledge area of data	Indictor	MO (n)	Nurse (n)	Resident (n)	Specialist (n)	N	Mean rank	H, (d.f), p-value
Collection	Poor	11	8	5	5	28	44.98	H=6.409 (1) p=0.011*
	Good	0	47	1	0	48	34.72	
Analysis	Poor	11	17	4	5	37	43.39	H=5.937 (1) p=0.015*
	Good	0	38	1	0	39	33.86	

Presentation	Poor	11	28	5	5	49	41.73	H=4.966 (1) p=0.026*
	Good	0	27	0	0	27	32.63	
Use	Poor	9	42	4	2	57	42.11	H=10.197 (1) p=0.001*
	Good	2	13	1	3	19	27.68	

*Significant result

Level of skills

A Kruskal-Wallis H test showed that there was a statistically significant difference in routine data use between those who had poor skills and good skills in data collection, H= 4.495 (1) p=0.034, with a mean rank routine data use score of 43.93for poor skills and 35.33for good skills. For the case of skills on data analysis, results showed a statistically significant difference in routine data use between those who had poor skills and good skills in data analysis, H=10.133 (1) p=0.001, with a mean rank routine data use score of 43.67for poor skills and 31.00 for good skills. Significance difference in routine data use was also revealed in skills on data presentation, H=8.006 (1) p=0.005, with a routine data use score of 42.49 for poor and 30.83 for good skills. Lastly, skills on data use had a significant difference in routine data use, H= 8.388 (1) p=0.004 between those with poor skills and good skills. The mean rank routine data use score for poor skills was 41.66 and 28.33for good skills. Specialists appeared to have good skills on data use compared to other categories whereas, two out of five had good skills on data use.

Table 5: Statistics of data use versus level of skills

Skills area of data	Indictor	MO (n)	Nurse (n)	Resident (n)	Specialist (n)	N	Mean rank	H, (d.f), p-value		
Collection	Poor	6	20	1	1	28	43.93	H	4.495 (1) p=0.034*	
	Good	5	35	4	4	48	35.33			
Analysis	Poor	9	32	2	2	45	43.67	H	10.133 (1) p=0.001*	
	Good	2	23	3	3	31	31.00			
Presentation	Poor	8	36	3	3	50	42.49	H	8.006 (1) p=0.005*	
	Good	3	19	2	2	26	30.83			
Use	Poor	9	42	4	3	58	41.66	H	8.388 (1) p=0.004*	
	Good	2	13	1	2	18	28.33			

*Significant result

Discussion

The study revealed a partial use of routine health data for decision-making. Partial use of these data does not show a good sign of positive information culture. As the study showed 61.6% use of routine health data for decision making, this proportion is higher compared to the study done in Uganda (59%) (Gladwin et al., 2003) and lower compared to the study done in South Africa (65%) (Garrib et al., 2008) and Ethiopia (78.5%) (Dagnew et al., 2018). The difference might be because of varieties in study periods and the standards for estimating routine wellbeing data use.

The main area of routine health data use reported by the health workers was the budget preparation (69.2%) and the least was planning clinical services (53.6%). However, these results are in contrast with the studies done in Tanzania by (Harrison & Bakari, 2008) and (Measure Evaluation, 2017) as they showed that most staff reported using routine health information for program related management especially planning, monitoring, medical supply and drug management.

It was also revealed that working experience (years), job title, and level of education were associated with the use of routine data for decision-making. Participants with Master's and specialists training reported to have excellent level of data use for decision-making. These findings suggest that education is likely to have association with using routine health data for making decisions.

Furthermore, there were statistically significant differences in data use between participants with poor and good levels of knowledge in data collection, analysis, presentation and use. These findings imply that knowledge is a crucial factor that affects the ability to use routine data for decision-making. This statement is supported by (Harrison & Bakari, 2008). There is a need to improve information-use practices and added skills on analysis and information utilization, and mentorship to all involved health workers.

The study also reported a significant difference in data use between health workers with poor and good levels of skills in data collection, analysis, presentation, as well as use. Results showed that majority had poor level of skills in areas of analysis, presentation, and data use. Poor level of skills in these areas might have contributed to the partial use of routine health data for decision-making. These findings are supported by (Hotchkiss et al., 2012) as they reported that, insufficient skills to analyze and usedata is among the constraints facing routine information system in developing countries. Standardized and comprehensive HMIS training programs should be developed and implemented for staff involved in data collection, aggregation, storage, and use. It should include pre-service, on-the-job, and supplementary training (NEP, 2017). Data users and data producers need to be trained in data aggregation, transmission, processing, and analysis and use of information to make informed decisions (Edwards, 2006).

Conclusion: The study revealed data use for decision making in the Emergency Medicine Department (EMD) had a rating score of 61.6%, which mostly is being used in budget preparation and staffing decisions. The culture of information use has been poorly promoted by department supervisors. Individual capacities in terms of the level of knowledge and showed differences in routine health data use for decision making between respondents who had a poor level of knowledge and skills and those with a high level of knowledge and skills in areas of data collection, analysis, presentation, and use.

There is a need to develop a framework for statistical capacity building in Tanzania, train a cadre of health workers with core competencies and skills in measuring progress in the health system that could generate a sustainable demand for data use within the health systems of the country. Interest and enthusiasm for using data in the department should be induced to all staff through demonstrating how data can enhance their working performance, improve patients' outcomes, and improve overall quality of their work experience.

Declaration

Ethical consideration: Ethical approval from the Muhimbili University of Health and Allied Sciences (MUHAS), Institutional Review Board (IRB) was granted for this study (Ref.No.MU/PGS/SAEC/Vol. IX). Permission to carry out the study in Muhimbili National Hospital at Emergency Medicine Department was obtained from the Executive Director through the head of Training Research and Consultants (TRC). The purpose of the study was explained to participants and written informed consent sought before the interview.

Authors' Contribution: MM contributed in conception, overseeing the manuscript write up and editing. SM contributed from conception, data collection, data analysis, and manuscript writing.

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