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Routine health data use for decision making and its associated factors among primary healthcare managers in dodoma region

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Abstract

Background Data demand and use culture have a tremendous impact on the proper allocation of scarce resources and evidence-based decision making. However, primary healthcare managers in the majority of Sub-Saharan African countries continue to struggle with using routine health data for decision-making.

Purpose/objective This study aimed to assess routine health data use for decision making among primary healthcare managers in Dodoma region.

Methods Cross-sectional study design involved 188 primary healthcare managers from Dodoma City Council, Kondoa Town Council and Bahi District Council was conducted. A self-administered questionnaire adapted from the Performance of Routine Information System Management (PRISM) tools was used to collect the data. Data was analysed by using the Statistical Package for Social Science (SPSS) program. Principal Component Analysis was used to find the level of routine health data use, binary logistic regression analysis was used to determine factors associated with routine health data use for decision making among primary healthcare managers. The study was conducted from May to June, 2022.

Results The level of adequate routine health data use for decision making among healthcare managers was 63.30%. Factors associated with adequate routine health data use for decision making among healthcare managers were; respondents characteristics: years of working experience (OR = 1.955, 95% CI= [0.892,4.287]), district surveyed (OR = 4.760, 95%CI= [1.412,16.049]), level of health facility (OR = 3.867, 95%CI= [1.354,7.122]) and male gender (OR = 1.901, 95%CI= [1.027,3.521]). Individual factors: comparing data with strategic objectives (OR = 2.986, 95%CI= [1.233–7.229]), decision based on health needs (OR = 7.330, 95%CI= [1.968–27.295]) and decision based on detection of outbreak (OR = 3.769, 95%CI= [1.091–13.019]). Technical factors: ability to check data accuracy (OR = 3.120, 95%CI= [1.682–5.789]), ability to explain findings and its implication (OR = 2.443, 95%CI= [1.278–4.670]) and ability to use information to identity gaps and targets (OR = 2.621, 95%CI= [1.381–4.974]). Organizational factors: organizational support (OR = 3.530, CI= [1.397–8.919]), analyse data regularly (OR = 2.026, 95%CI= [1.075–3.820]) and displays information on key performance indicators (OR = 3.464, 95%CI= [1.525–7.870]).

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Conclusion and recommendation The level of routine health data use for decision making among primary healthcare managers was found to be modest. The level of data demand and use culture may increase more quickly if capacity building is strengthened and issues that de-motivate primary health care managers from using data are addressed.

Keywords Routine health data, Primary healthcare managers, Decision making, Health information, Associated factors

Background

Globally, Health Information system is an important engine toward planning, management, evaluation and decision making to all World Health Organization (WHO) health building blocks [1]. It is easier to plan, make policies, implement, monitor, and evaluate health programs at any level in sub-Saharan African nations when accurate and trustworthy health information is available [2, 3]. In the year 2000s, countries in Sub-Saharan Africa adopted the District Health Information System (DHIS2) as a way to improve the Health Management Information System (HMIS) and expand the use of health information [4]. One of the health reforms implemented to enhance service delivery at the point of care is the strengthening of the Health Management Information System (HMIS) and decentralization policy [5, 6]. This policy gives lower health managers a decision making autonomy toward resource management and implementation of various interventions [7]. Additionally, the policy encourages community engagement in health planning, an improvement in service quality, and social equity [8, 9]. With the aid of HMIS, lower-level health managers are able to prioritize issues, allocate resources, monitor progress, and carry out other managerial tasks [10]. As a primary source of all data in the health sector, Tanzania introduced HMIS in the 1990s [11], which is made up of paper-based and electronic systems that collect data on health interventions carried out and health services delivery reports from patients and the community [12].

Healthcare managers can measure the magnitude of disease morbidity and mortality in the population, monitor trends over time, detect any outbreak and take appropriate action quickly using routine health data, collected from the community and patients during service provision [13, 14]. In Tanzania's primary healthcare facilities, paper-based systems, such as MTUHA books, report forms, partner's project registers, and electronic systems, are most frequently used [15]. Prior to the implementation of the decentralization policy, the ability of primary healthcare managers to manage primary healthcare facilities was constrained. Instead, data were gathered at the facilities, combined, summarized into summary sheets, and submitted to the council levels for further action [16]. Then, councils were in charge of entering data into the DHIS2 electronic system, analysing data, interpreting data, and generating reports as necessary [17]. Various decisions, such as resource allocation and projections of all health facility activities for respected councils and the council itself, were anticipated to be informed by the information obtained [14]. Due to decentralization brought about by devolution policy, primary healthcare managers now have more decision-making authority. Currently, facilities have the authority to develop an annual health plan, decide how to use the funds that have been received, and manage those funds [18, 19]. As a result, electronic systems were introduced at the facility level, including the planning and reporting system (PLANRep), the government of Tanzania's health operational management information system (GOTHOMIS), the facility financial accounting and reporting system (FFARS), the integrated monitoring and evaluation system (iMES), the electronic logistic management information system (eLMIS), and partner systems that were used to collect project information, enhance healthcare services and increase revenue [20, 21]. In order to ensure transparency and accountability at all levels in light of this data demand culture, dissemination and use should be increased [22].

Despite of various initiatives taken by most of developing country's governments to improve HMIS, including introduction of electronic system that facilitate bulk of data collection at the lower levels, data use practices have been reported to remain as an issue [1, 23, 24]. Studies have reported that electronic and paper-based systems are not fully integrated, that result to absence of data merging and aggregation, inconsistence of data from different systems and increase work burden to the healthcare workers [10, 12, 15, 25]. The fact that these factors contribute to generation of poor quality data, using poor quality data for decision making results inbad decisions, which health care systems in developing countries must address [26]. In order to make the best decisions and achieve better health outcomes from the various health interventions used in the health care sector, it is crucial to identify the potential factors affecting Routine Health Information System (RHIS) performance. Inadequate data analysis skills, computer use, and a lack of standard operating procedures (SOPs) for data management are reported as contributing factors toward inadequate use of routine health data for decision making [13]. The Performance of Routine Information System Management

(PRISM) framework describes the aforementioned factors which can be divided into organizational, technical, and individual factors as the primary determinants of RHIS performance [12]. In order to design interventions and create strategies for enhancing HIMS performance, policy makers and program planners would benefit from researching the extent to which routine health data are used by healthcare managers for decision-making. Despite the implementation of a decentralisation policy aimed at providing primary healthcare managers more authority to improve service delivery at primary healthcare facilities, there are few studies that directly quantify the use of data for decision-making in the management of Primary Health Care (PHC) facilities in Tanzania. Therefore, this study aimed to assess the level of routine health data use for decision making among primary healthcare managers and factors associated with it in Dodoma region.

Methods

Study design

A cross-sectional study was conducted using quantitative approachThe study was carried out between May and June of 2022.

Study sites and settings

The research was carried out in the Dodoma region, which has seven districts. This study included three districts: Bahi District Council, Kondoa Town Council, and Dodoma City Council. According to the star-rating of health facility service delivery quality improvement report of 2017/2018 conducted by Ministry of Health Community Development, Gender, Elderly and Children (MoHCDEC), Dodoma Region was among the regions that performed poorly, because 14 Primary Healthcare facilities received 0 stars, 112 received 1 star, and 184 PHC facilities received 3 stars [27]. As a result, the Dodoma region was chosen for this study to investigate whether poor service delivery is influenced by the level of routine health data use for decision making. The three districts involved in the study was selected as regional representatives of each district's distinctive characteristics with regard to its location in the region. Dodoma City Council is a metropolitan city with ample resources to promote effective data use. Bahi District Council, located on the outskirts of the region, was chosen to represent rural districts. Kondoa Town Council was chosen to represent town councils. Dodoma Region has 16 districts hospitals, 47 health centres, and 373 dispensaries that provide primary healthcare services to the community.

Study population

The study includes all healthcare managers who make decisions in various departments/sections of public primary healthcare facilities, this includes; medical officer in-charge, health secretary, nursing officer in-charge, HMIS focal person and heads of the following departments; out patient department (OPD), Tuberculosis (TB), HIV/AIDS care and treatment clinic (CTC), reproductive and child health (RCH), immunization, eye, pharmacy, laboratory, x-ray and dental. Managers with more than one year of experience, who were available at the time of data collection and agree to participate were included in the study. Participants who were acting on behalf of their managers were excluded from the study.

Sample size, sampling methods and procedures

The sample size was determined using the Yamane formula [28], with a 95% confidence interval, a 5% margin of error, and a 13% non-response rate, yielding a total of 188 respondents. Based on the number of healthcare managers available in each district, the estimated sample size was divided among three districts. The Bahi district had 140 healthcare managers, Dodoma City had 144, and Kondoa Town had 30. As a result, the total number of healthcare managers in the selected districts was 314. A proportionate formular was used to sample 84 healthcare managers from Bahi District, 86 from Dodoma City, and 18 from Kondoa Town Council. Because each district has one district hospital and a few health centres, the study included all healthcare managers from district hospitals and health centres. Since each district hospital has ten healthcare managers, the three districts have a total of thirty (30) healthcare managers. Each health centre employs eight (8) healthcare managers. The Bahi district has six (6) health centres, for a total of 48 healthcare managers. Dodoma City has four (4) health centres, totaling 32 healthcare managers, while Kondoa Town Council has one (1) health centre, totaling eight healthcare managers. As a result, 118 healthcare managers from district hospitals and health centres were selected. The remaining 70 healthcare managers were chosen at random from dispensaries. A proportionate formular was used to allocate healthcare managers from each dispensary in the district. There are 34 dispensaries in Bahi District, 32 in Dodoma City, and 5 in Kondoa Town Council. Each dispensary is supposed to have two healthcare managers, but in Bahi District, two dispensaries were found to only have one. As a result, the Bahi district had 68 healthcare managers, while Dodoma City had 64 and Kondoa Town Council had 10. A proportionate formular was used to select 17 dispensaries at random from Bahi District, 16 from Dodoma City, and three from Kondoa Town Council. (Supplementary material 1).

Data collection tools and procedures

To obtain data, a self-administered questionnaire with closed questions was employed. The questionnaire was adapted from earlier research [15, 29, 30] and the PRISM framework on data demand and utilization [31]. This was based on the study's purpose, an exhaustive literature assessment, and pertinent local circumstances. The Questionnaire was divided into five parts, part one: captured respondents' background characteristics. Part two: collected data on the pattern of routine health data use. Part three: captured technical factors of routine health data use. Part four: obtained information on organizational factors associated with routine health data use, and part five: assessed individual factors associated to routine health data use. Prior to data collection the questionnaire was pretested with 10 healthcare managers from Chamwino District, which has characteristics similar to the three districts selected for the study. It was then modified to meet the study environment. To ensure content related validity, the questionnaire was translated into Swahili and then back into English by two professional experts who were fluent in both Swahili and English. The questionnaire was critically evaluated by two additional experts in the field in order to establish face validity.

Study variables

The outcome variable was the use of routine health data for decision making. The variable was defined as the proportion of healthcare managers who make decisions based on routine health data. This was built with the help of eleven core indicators identified by the PRISM tool [31]. The indicators used to assess the level/extent of routine health care were planning, monitoring, and evaluation, identification of gaps and priority areas, prediction and detection of outbreaks, review strategy by examining service performance targets, mobilization/shifting of resources based on service comparison, ensuring efficient and effective use of limited resources, medical supply and drugs management, procurement of medicines and health commodities, and staffing decisions. The indicators were assessed using a four Likert scale in which participants rated themselves on whether they perform the core mentioned indicators always, sometimes, rarely, or never. The indicators were subjected to principal component analysis in order to determine how much they contribute to the use of routine health data for decision making (Fig. 1). The scores were calculated with the mean score as a cutoff point, participants scoring above the mean value were considered to have "adequate level of routine health data use" for decision making, while those scoring below the mean value were considered to have "inadequate level of routine health data use" for decision making. Previous studies had similar categorization [10, 29, 30, 32].

The independent variables were: Social demographic characteristics (age, gender, level of education, position, department name, work experience, facility type, district type, and professional training). Technical factors (trainings, competence, data availability and data collection tools), organizational factors (roles and responsibilities, supportive supervision, meetings and feedback), and individual factors (decision making basis, barriers, motivators and de-motivators).

Data processing and analysis

SPSS version 26 was used to analyse the data. Eleven (11) Likert scale questions (indicators) with 1 to 4 scales each were used to determine the extent/level of routine health data use. The pattern of routine health data use was then obtained using Principal Component Analysis (PCA). Based on the Kaiser's recommendation [31, 33]. the analysis then extracts two factors with eigenvalues of 1.0 and above. One (1)indicator, "procurement of medicine and health commodities," was removed from the factor analysis because it had a weak association with routine health data use for decision making. The remaining ten (10) indicators were used to determine the level of routine health data use for decision making, with scores obtained and the mean score used as a cutoff point to determine the level of routine health data use for decision making. The pattern number one was used as the basis for the mean, with a weight of 50.17% (Fig. 1). Participants who scored higher than the mean (>50.17%) were considered to have an "adequate level of routine data use," while those who scored lower were considered to have an "inadequate level of routine data use" (Fig. 2). Binary logistic regression was used to assess factors associated with routine data use and a p-value < 0.05 was considered statistically significant.

Ethical approval on the study

The University of Dodoma's ethical committee was contacted for an ethical clearance letter, and permission to visit the health facilities was obtained from the President's Office, Regional Administration and Local Government Authority (PO-RALG), and Local Government Authorities (LGAs). Before administering the questionnaires, respondents were asked to consent. The research was beneficial because it did not harm any respondents and instead promoted the welfare of our constituents. The researcher protected the identity of the participants by giving unique number to all questionnaires instead of writing their names and any other identity in order to maintain confidentiality of the participants. The data collected in this study was used only for the purpose of this study.

Results

Social demographic characteristics of study participants

This study involved 188 respondents from three districts. About 107 (56.91%) of respondents were female, with 91

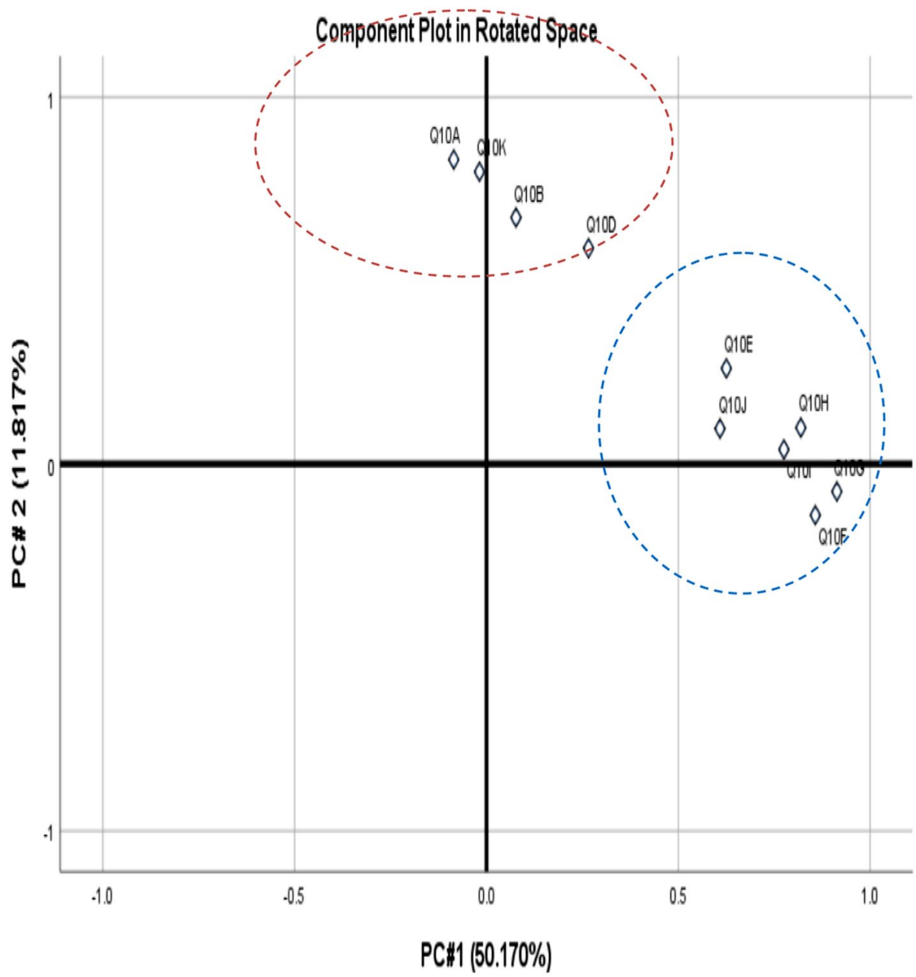

Fig. 1 PCA loading plot showing a pattern of routine health data use for decision making among primary healthcare managers. Key: Q10A is planning, Q10B is monitoring and evaluation, Q10C is identification of gaps and priority areas, Q10D is a prediction and detection of outbreak, Q10E is a review strategy by examining service performance target and Q1OF is a mobilization/shifting of resources based on comparison by services. Furthermore, Q10G is ensuring efficient and effective use of limited resource, Q10H is a medical supply and drugs management, Q10I is a procurement of medicines and health commodities, Q10J is a staffing decision and Q10K is service delivery improvement.

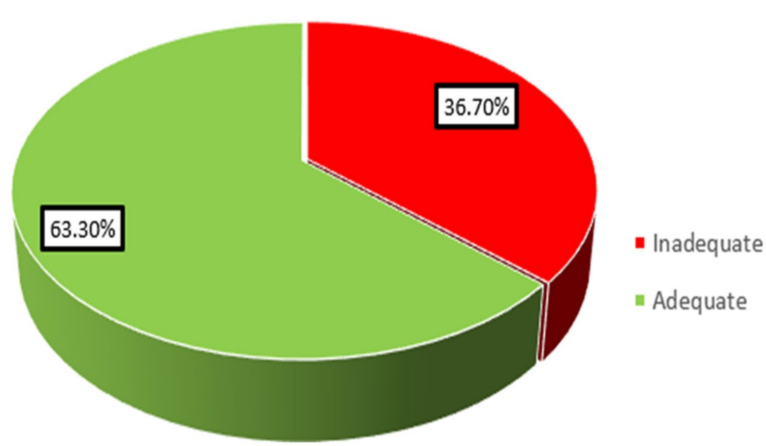

Fig. 2 Overall level of routine health data use for primary healthcare managers in Dodoma region

(48.40%) ranging in age from 30 to 39 years. The majority of 137 (73.66%) acquired a diploma as the highest level of education. Nearly half of the respondents, 83(44.15%), worked in dispensaries, with nurses leading the way 78(43.82%), followed by clinical officers 43 (24.16%). With regard to working experience 76 (40.43%) of respondents had 5 to 10 years of experience (Table 1).

Pattern of routine health data use for decision making among primary healthcare managers

Table 2 depicts the pattern of routine health data use for decision making. More than half 56 (84%) of respondents reported using routine health data "always," 24 (12.90%) reported using routine health data "sometimes," 5 (2.69%) reported using routine health data "rarely," and 1 (0.54%) reported "never" using routine health data. Data use for the procurement of medicines and health commodities was reported as follows: "always" 145 (79.23%), "sometimes" 22 (12.02%), "rarely" 16 (3.28%), and "never" 10 (5.46%). For staffing decision, respondents who reported to use routine health data were; always 112 (60.87%), sometimes 48 (26.09%) and respondents who "never" use routine health data for staffing decisions were 13 (7.07%). Other variables are shown in Table 2.

Table 1 Social demographic characteristics of study participants ($N=188$)

Variables	Frequency (*n*)	Percent (%)
Gender		
Male	81	43.09
Female	107	56.91
Age in years		
21–29	45	23.94
30–39	91	48.40
40–49	38	20.21
50+	14	7.45
Highest education attained		
Form four	5	2.69
Certificate	17	9.14
Diploma	137	73.66
Degree and above	27	14.52
Professional training		
Doctor	20	11.24
Nurse	78	43.82
Clinical Officer	43	24.16
Others (Lab technicians, Pharmacist, AMO, CO, HMIS focal)	37	20.78
Position of respondents in the facility		
Facility In charge	30	16.13
Administrators	14	7.52
In charge of section	142	76.35
Work experience (years)		
1–5	65	34.57
5–10	76	40.43
11+	47	25.00
Experience on current position		
< 5	121	64.36
5–10	50	26.60
11+	17	9.04
District surveyed		
Dodoma CC	84	44.68
Kondoa TC	18	09.57
Bahi DC	86	45.74
Type of facility		
District hospital	29	15.43
Health centre	76	40.43
Dispensary	83	44.15

Table 2 Descriptive analysis for extent of routine health data use for decision making

Variable	Never *N* (%)	Rarely *N* (%)	Sometimes *N* (%)	Always *N* (%)	Mean ± SD
Planning	2 (1.07)	8 (4.28)	30 (16.04)	147 (78.61)	2.76 ± 0.54
Monitoring and Evaluation	0 (0.00)	11 (5.88)	28 (14.97)	148 (79.14)	2.73 ± 0.54
Identification of gaps and priority areas	3 (1.60)	9 (4.81)	40 (21.39)	135 (72.19)	2.71 ± 0.58
Prediction and detection of outbreak	8 (4.42)	14 (7.73)	36 (19.89)	123 (67.96)	2.69 ± 0.68
Review strategy by examining service performance target	2 (1.11)	7 (3.89)	36 (20.00)	135 (75.00)	2.73 ± 0.55
Mobilization/Shifting of resources based on comparison by services	3 (1.66)	8 (4.42)	38 (20.99)	132 (72.93)	2.72 ± 0.57
Ensuring efficient and effective use of limited resource	1 (0.56)	6 (3.37)	42 (23.60)	129 (72.47)	2.70 ± 0.54
Medical supply and drugs management	6 (3.31)	6 (3.31)	27 (14.92)	142 (78.45)	2.82 ± 0.53
Procurement of medicines and health commodities	10 (5.46)	6 (3.28)	22 (12.02)	145 (79.23)	2.87 ± 0.54
Staffing decisions (Deployment, review personnel responsibilities)	13 (7.07)	11(5.98)	48 (26.09)	112 (60.87)	2.69 ± 0.69
Service delivery improvement	1 (0.54)	5 (2.69)	24 (12.90)	156 (83.87)	2.82 ± 0.46
overall use	**0(0.00)**	**5 (2.67)**	**29 (15.51)**	**153 (81.82)**	**2.79 ± 0.47**

Principal component analysis to describe pattern of routine health data use

Figure 1 depicts a loading plot containing the two significant principal components (PCs) of the pattern of routine health data use, from which the un-rotated factor solution retained two (2) factors that explained 61.99% of the total variance. The first factor, administrative issues (labelled as PC1 in the figure), accounted for about 50.17% of routine health data use. Monitoring and evaluation, referred to as principal component two (PC2), accounted for 11.82% of routine health data use (Fig. 1). PC1 contrasts question Q10A (Planning) and Q10K (Service delivery improvement), which were highly correlated on one side. Q10B (monitoring and evaluation) and Q10D (prediction and detection of outbreak) on the other side. PC 2 distinguished between questions Q10F (Resource mobilization/shifting based on service comparison) and Q10G (Ensuring efficient and effective use of limited resources). The plot generally revealed two groups of highly correlated variables: group one with questions 10 A (Planning), 10 K (Service delivery improvement), 10 B (monitoring and evaluation), and 10 D (prediction and detection of outbreak), and group two with highly correlated questions 10 A (Planning), 10 K (Service delivery improvement), 10 B (monitoring and evaluation), and 10 D (prediction and detection of outbreak). As shown in Figs. 1 and 10E and E (review strategy by examining service performance targets), 10 J (staffing decisions), 10 H (medical supply and drug management), 10 C (identification of gaps and priority areas), 10 F (mobilization/shifting of resources based on service comparison), and 10 G (ensuring efficient and effective use of limited resources) are all priorities. The principal component analysis resulted in an overall pattern of routine health data use, revealing that 63.30% of respondents used routine health data adequately for decision-making (Fig. 2).

Factors contributing to routine health data use for decision making among primary healthcare managers

Table 3 shows the results of the factors that influence primary healthcare managers' use of routine health data for decision making. Technical factors thought to influence routine health data use for decision making were assessed and it was found that respondents received HMIS training in the following areas: Less than half (89.34%) of respondents received training on data collection and reporting, more than a quarter (75.89%) received training on data analysis, 88 (46.81%) received training on data presentation, and 74 (39.36%) received training on electronic health information systems such as DHIS2 and GoTHOMIS. In regards to the ability to carry out various HMIS activities; nearly three quarters 134 (71.28%) of respondents reported an ability to explain findings and their implications and 131 (69.68%) reported an ability to use information to identify gaps and set targets. More than half 107(57.83%) of the respondents reported adequate competency in information management tasks. The majority 167(90.27%) of respondents agreed that, they have access to routine health data, and majority 180(97.30%) of respondents agreed that they have access to data collection registers (MTUHA books) (Table 3).

For organizational factors, the majority 156 (90.15%) of respondents reported receiving a high level of support for data management. More than half 116 (63.74%) of the respondents said their job descriptions clearly defined their roles and responsibilities. About three quarters 130(70.66%) of respondents reported to analyse data in their departments. Only 22 (12.15%) of healthcare managers displays information on key performance indicators on notice boards. In terms of conducting departmental meetings, 31(16.76%) of respondents report doing so on a weekly basis. In addition, 173 (92.51%) of respondents said they had received supportive supervision visits (Table 3).

Table 3 Technical, organizational and individual factors for routine health data use

Variable	Yes (%)	No(%)
Technical factors		
Trainings received on		
Data collection and reporting	89(47.34)	99(52.66)
Data analysis	75(39.89)	113(60.11)
Data presentation	88(46.81)	100(53.19)
Electronic Health information systems (i.e. DHIS2, GOTHOMIS)	74(39.36)	114(60.64)
Ability to carry out HMIS activities		
Check data accuracy	114(60.64)	74(39.36)
Calculate percentage/rates	117(62.23)	71(37.77)
Plot information by months	130(69.15)	58(30.85)
Explain findings and their implications	134(71.28)	54(28.72)
Use information to identity gaps and targets	131(69.68)	57(30.32)
Level of competence in information management task	107(57.83)	79(42.70)
Access to routine data/health information	167(90.27)	18(9.23)
Availability of data collection registers (MTUHA books)	180(97.30)	5(2.70)
Access to functional equipment		
Computer	135(72.97)	50(27.03)
Printer	102(55.14)	83(44.86)
Calculator	65(35.14)	120(64.86)
Data backup unit (flash etc.)	85(45.95)	100(54.05)
Internet	101(54.59)	83(45.41)
Organizational factors		
Level of support on data management received		
Low	18	9.79
High	156	90.15
Roles and responsibilities on data use clearly defined in job description		
Not well	66	36.26
Well	116	63.74
How often do you analyse the collected data		
Rarely	54	39.35
Always	130	70.66
Display of information on key performance indicators		
Yes	22	12.15
No	159	87.84
How frequently do you hold departmental meeting		
No schedule	2	1.08
Weekly	31	16.76
Monthly	125	67.57
Quarterly	19	10.27
Facility visited for supportive supervision last Quarter	173	92.51
Supervisor had a checklist to assess the data use	162	86.63
Supervisor help you make a decision based on routine health data	145	77.54
Supervisor gave you feedback on last three supervisory visit	157	83.96
Supervisor gave you written feedback for supportive supervision	157	83.96
Individual factors		
Basis of decision made (to what extent your managerial decisions are based on)		
Personal liking	60(31.91)	128(68.09)
Superiors' directives	130(69.15)	58(30.85)
Information/evidence	147(78.19)	41(21.81)
Job experience	132(70.21)	56(29.79)
Considering cost	108(57.45)	80(42.55)
Comparing data with strategic health objectives	143(76.06)	45(23.94)
Political interference	37(19.68)	151(80.32)

Table 3 (continued)

Variable	Yes (%)	No(%)
Motivators (What motivate you from using routine health data for decision making?)		
Job promotion	151(80.32)	37(19.68)
Training/mentorship	167(88.83)	21(11.17)
Good ICT infrastructure	154(81.91)	34(18.09)
Incentives	154(81.91)	34(18.09)
Supportive supervision	167(88.83)	21(11.17)
Availability of tools/ equipment	166(88.30)	22(11.70)
Payment for performance	149(79.26)	39(20.74)
Presence of electronic health information systems i.e. DHIS2 and GOTHOMIS	134(71.28)	54(28.72)
De-motivators (What de-motivate you from using routine health data for decision making?)		
High workload	149(79.26)	39(20.74)
Too much paper based	157(83.51)	31(16.49)
Poor internet connectivity	151(80.32)	37(16.68)
Lack of feedback	136(72.34)	52(27.66)
Inadequate equipment/ tools	149(79.26)	39(20.74)
Insufficient skilled personnel	155(82.45)	33(17.55)
Poor documentation	147(78.19)	41(21.81)
Lack of national guideline for data use	141(75.00)	47(25.00)
Barriers encountered when using RH data		
Incomplete data	103(55.98)	77(44.02)
Poor quality data	91(49.46)	93(50.54)
Data was produced late	52(28.26)	130(71.74)
Data not well presented	43(23.37)	141(76.63)
Data not available	26(14.13)	154(85.87)
No problem	36(19.57)	152(80.43)
Feedback provided on barriers	141(76.63)	43(23.37)
Issue addressed	103(55.98)	70(44.02)

Factors associated with adequate routine health data use among primary healthcare managers

For individual factors it was found that respondent's decisions making in their daily activities was based on following; comparing data with strategic health objective 143 (76.06%), information/evidence 147 (78.19%), job experience 132 (70.21%), superior directives 108 (69.15%), considering cost 108 (57.45%) and respondents who use political interference were 37 (19.68%). Based on individual motivations for using routine health data, it was discovered that, majority 167 (88.83%) of respondents reported to be motivated by trainings/mentorship, 151 (80.32%) by job promotion, 154 (81.91%) by availability of good ICT infrastructures,154 (81.91%) by incentives, 167 (88.83%) by supportive supervision, 147 (79.26%) by payment for performance and 134 (71.28%) respondents reported to be motivated by presence of electronic health system (DHIS2 and GOTHOMICS). Moreover, most of respondents were de-motivated to use routine health data for decision making by factors such as; too much paper based 157 (83.51%), insufficient skilled personnel 155 (82.45%), poor internet connectivity 151 (80.32%), heavy work load 149 (79.26%), in adequate equipment 152 (79.26%), poor documentation 147 (78.19%) and lack of national guideline for data use 141 (75.00%). In regard to barriers to routine health data use, more than half 103(55.98%) of respondents reported incomplete data as a barrier, and nearly half 91(49.46%) reported poor data quality. More than a quarter 52(28.26%) reported late data as a barrier, less than a quarter 43(23.37%) reported data not well presented and data not available at all 26(14.13%) as common barriers encountered by healthcare managers when using routine health data for decision making, and only a few 36(19.57%) respondents reported no problems when using routine health data (Table 3).

Factors associated with adequate routine health data use for decision making among primary healthcare managers

Selected characteristics of respondents

A multivariate logistic regression analysis was used to determine the relationship between the characteristics selected from respondents and the use of routine health data for decision making (Table 4). Respondents with less years of work experience were nearly two (2) times more likely to use routine health data for decision making compared to workers with more years of work experience. (OR=1.955, CI= [0.892,4.287], p=0.0941). In terms of the districts surveyed, healthcare managers from Kondoa TC were more likely to use routine

Table 4 Binary logistic regression analysis for selected characteristics of respondents associated with adequate routine health data use among primary healthcare managers

Variable	Unadjusted logistic regression		Adjusted logistic regression	
	OR [95%CI]	*p*-value	AOR [95%CI]	*p*-value
Age in years				
21–29	2.214[0.652,7.523]	0.2027		
30–39	1.844[0.594,5.722]	0.2897		
40–49	1.375[0.402,4.703]	0.6118		
50+	**Ref**			
Work experience (yrs)				
1–5	1.955[0.892,4.287]	0.0941	1.264[0.523,3.056]	0.6027
5–10	1.309[0.626,2.739]	0.4746	1.250[0.549,2.850]	0.5949
11+	**Ref**		**Ref**	
Experience on current position (yrs)				
1–5	1.105[0.381,3.202]	0.8547		
5–10	0.640[0.205,2.001]	0.4433		
11+	**Ref**			
District surveyed				
Dodoma CC	0.935[0.455,1.920]	0.8548	0.582[0.259,1.305]	0.1886
Kondoa TC	4.760[1.412,16.049]	0.0119	4.426[1.137,17.237]	**0.0320**
Bahi DC	**Ref**		**Ref**	
Level of facility				
District hospital	3.867[1.354,7.122]	0.0141	2.680[1.926,6.147]	**0.0062**
Health centre	2.594[1.311,4.137]	0.0360	1.864[0.220,5.979]	0.0639
Dispensary	**Ref**		**Ref**	
Gender of respondent				
Male	1.901[1.027,3.521]	0.0410	1.500[0.733,3.069]	0.2670
Female	**Ref**		**Ref**	

health data for decision making compared to workers from other districts. (OR = 4.760, CI= [1.412,16.049], $p = 0.0119$). Based on level of facility, healthcare managers from district hospital were nearly four (4) times more likely to use routine health data for decision making compared to workers from dispensaries (OR = 3.867, CI= [1.354,7.122], $p = 0.0141$). Healthcare managers from health centers were nearly three (3) times more likely to use routine health data for decision making compared to workers from dispensaries (OR = 2.594, CI= [1.311,4.137], $p = 0.0360$). Being a male gender was associated with higher odds of using routine health data for decision making compared to female (OR = 1.901, CI= [1.027,3.521], $p = 0.0410$). After controlling for confounding variables (age), the facility level and district surveyed remained statistically significant factors of routine health data use for decision making. With regards to level of facility, respondents working at district hospitals were nearly three (3) times more likely to use routine health data compared to those who worked at dispensaries and health centers (A0R = 2.680, C1= [1.926,6.147], $p = 0.0062$), Being a healthcare manager from Kondoa TC was associated with higher odds of using routine health data for decision making compared to healthcare managers from Dodoma CC and Bahi DC (AOR = 4.426, CI= [1.137,17.237] $p = 0.0320$).

Individual, technical and organizational factors associated with adequate routine health data use for decision making

Individual factors

The variables of interest were subjected to multivariate logistic regression analysis (Table 5) to determine the relationship between adequate routine health data use for decision making and individual factors. It was found that respondents who reported making decisions by comparing data with strategic health objectives were nearly three (3) times more likely than their counterparts to use routine health data (OR = 2.986, CI= [1.233–7.229], $p = 0.0153$). In terms of information basis, respondents who reported making decisions based on available information were two times more likely compared to their counterparts to use routine health data (OR = 2.166, CI= [1.072–4.373], $p = 0.0312$). Making decisions based on job experience increases the odds of adequate routine health data use; respondents who reported making decisions based on their job experience were more likely to have adequate use of routine health data for decision making than their counterparts (OR = 1.995, CI= [1.053–3.782], $p = 0.0342$). Making decisions based on health needs increases the odds of having adequate routine health data use, with respondents who reported making decisions based on health needs being seven (7) times more likely to have adequate routine health data use than those who reported not using health needs for decision making (OR = 7.330, CI= [1.968–27.295], $p = 0.0030$). The basis for adequate use of routine health data for decision making was found to be outbreak detection, with respondents who reported making decisions based on outbreak detection nearly four (4) times more likely to use routine health data for decision making compared to their counterpart (OR = 3.769, CI= [1.091–13.019], $p = 0.0359$).

Surprisingly, supervisors' directives and political interference were found to be inversely related to adequate routine health data use for decision making, with respondents who reported using supervisors' directives as their basis of decision making having greater odds of adequate routine health data use for decision making than their counterparts (OR = 2.026, CI= [1.075–3.820], $p = 0.0291$). Respondents who reported political interference in their decision making had a higher likelihood of using adequate routine health data for decision making than their

Table 5 Individual, technical and organizational factors associated with adequate routine health data use in health facilities

Variable	OR [CI 95%]	*p*-Value	AOR [CI 95%]	*P*-Value
Individual Factors				
Basis of decision making				
Superior's directives				
No	**Ref**		**Ref**	
Yes	2.026[1.075–3.820]	0.0291	0.643[0.220–1.879]	0.4195
Comparing data with strategic health objectives				
No	**Ref**		**Ref**	
Yes	2.986[1.233–7.229]	0.0153	4.905[1.352–17.796]	0.0156
Information/evidence				
No	**Ref**		**Ref**	
Yes	2.166[1.072–4.373]	0.0312	1.343[0.376–4.788]	0.6497
Job experience				
No	**Ref**		**Ref**	
Yes	1.995[1.053–3.782]	0.0342	1.756[0.692–4.457]	0.2364
Political interference				
No	**Ref**		**Ref**	
Yes	2.204[1.115–4.359]	**0.0230**	0.801[0.247–2.595]	0.7114
Health needs				
No	Ref		Ref	
Yes	7.330[1.968–27.295]	**0.0030**	9.440[1.290-69.076]	**0.0271**
Detection of outbreak				
No	**Ref**		**Ref**	
Yes	3.769[1.091–13.019]	**0.0359**	0.891[0.117–6.790]	0.9114
De motivators				
Inadequate equipment/ tools				
No	**Ref**		**Ref**	
Yes	2.354[1.232–4.497]	**0.0095**	0.781[0.289–2.107]	0.6252
Insufficient skilled personnel				
No	**Ref**		**Ref**	
Yes	2.248[1.202–4.204]	**0.0112**	2.012[0.719–5.633]	0.1833
Motivators				
Job promotion				
No	**Ref**		**Ref**	
Yes	2.449[1.179–5.086]	**0.0163**	2.578[0.913–7.277]	0.0737
Payment for performance				
No	Ref			
Yes	1.664[0.668–4.148]	0.2744		
Technical factors				
Ability to carry out HMI activities				
Check data accuracy				
No	**Ref**		**Ref**	
Yes	3.120[1.682–5.789]	**0.0003**	2.874[0.821–10.067]	0.0988
Plot information by months				
No	**Ref**		**Ref**	
Yes	3.534[1.892–6.604]	**0.0001**	9.532[1.839,49.398]	**0.0072**
Calculate percentage/rates				
No	**Ref**		**Ref**	
Yes	2.250[1.192–4.247]	0.0124	0.157[0.024–1.019]	0.0524
Explain findings and their implications				
No	**Ref**		**Ref**	
Yes	2.443[1.278–4.670]	0.0069	1.847[0.284–12.001]	0.5203
Use information to identity gaps and targets				
No	**Ref**		**Ref**	

Table 5 (continued)

Variable	OR [CI 95%]	*p*-Value	AOR [CI 95%]	*P*-Value
Yes	2.621[1.381–4.974]	0.0032	0.637[0.121–3.352]	0.5941
Organizational Factors				
Organizational Support received				
No	**Ref**		**Ref**	
Yes	3.530[1.397–8.919]	0.0076	0.803[0.212–3.036]	0.7464
Data analyzed regularly				
No	**Ref**		**Ref**	
Yes	2.026[1.075–3.820]	0.0291	1.461[0.618–3.456]	0.3878
Display of information on key performance indicators				
No	**Ref**		**Ref**	
Yes	3.464[1.525–7.870]	0.0030	2.897[0.866–9.691]	0.0843

counterparts (OR=2.204, CI= [1.115–4.359], p=0.0230). Similarly, it was found that respondents who are demotivated from using routine health data due to insufficient equipment were two (2) times more likely to have adequate use of routine health data for decision making than those who are not demotivated by insufficient equipment (OR=2.354, CI = [1.232–4.497], p=0.0095). Surprisingly, respondents who were demotivated to use routine health data due to insufficient skilled personnel were two (2) times more likely to have adequate use of routine health data for decision making than those who were not demotivated by insufficient skilled personnel. (OR=2.248, CI= [1.202–4.204], p=0.0112). Based to the motivators for adequate routine health data use for decision making, the odds of adequate routine health data use increase with job promotion, with respondents who reported being motivated by job promotion being two (2) times more likely than their counterparts (OR=2.449, CI= [1.179–5.086], p=0.0163).

to adjust for confounder effects, all variables were entered into the logistic regression model at the same time. The variables that remained significant associated with adequate routine health data use were comparing data with strategic objectives and using routine health data based on health need. The odds of adequate routine health data use increase when respondents compared data with strategic objective in decision making, with respondents who reported comparing data with strategic objective as their basis of decision-making being five (5) times more likely than their counterparts (AOR=4.905, CI= [1.352–17.796], p=0.0156). Regarding health needs, respondents who reported making decisions based on health needs were nine (9) times more likely compared to their counterparts to have adequate routine health data use for decision making (AOR=9.440, CI= [1.290-69.076], p=0.0271) (Table 5).

Technical factors

Technical factors significantly associated with adequate routine health data use were ability to check data accuracy, ability to plot information by month, calculate percentage, explain findings and their implications and use information to identity gaps and targets (Table 5). Respondents who reported to have ability of checking data accuracy were three (3) times more likely to have adequate routine health data use for decision making compared to those who reported to have no ability of checking data accuracy (OR=3.120, CI= [1.682–5.789], p=0.0003). The odds of adequate routine health data use for decision making increases with the ability to plot information by months, in which respondents who reported to have ability of plotting information by months had more odds of adequate routine health data use for decision making compared to their counterparts (OR=3.534, CI= [1.892–6.604], p=0.0001). Respondents who reported to have ability to calculate percentage had more odds of adequate routine health data use for decision making compared to their counterparts (OR=2.250, CI= [1.192–4.247], p=0.0124). The ability to explain findings and their implications increases the odds of adequate routine health data use for decision making; respondents who reported being able to explain the implications of their findings were two (2) times more likely to have adequate routine health data use for decision making than those who did not have the ability to explain their findings and their implications (OR=2.443, CI= [1.278–4.670], p=0.0069). Respondents who reported having the ability to use information to identify gaps and targets were more than twice as likely as their counterparts to have adequate routine health data use for decision making (OR=2.621, CI= [1.381–4.974], p=0.0032). After controlling for confounders, only the variable ability to plot information by month remained significantly associated with adequate routine health data use for decision making (AOR=9.532, CI= [1.839,49.398], p=0.0072).

Organizational factors

Table 5 shows that organizational support, data analysis on a regular basis, and information displays on key performance indicators were the organizational factors associated with adequate routine health data use for decision making. Respondents who reported receiving organizational support in routine health data use for decision making were three (3) times more likely than their counterparts to have adequate routine health data use for decision making (OR=3.530, CI= [1.397–8.919], p=0076). Respondents who reported their organization regularly analyses data were two (2) times more likely than their counterparts to have adequate routine health data use for decision making (OR=2.026, [1.075–3.820], p=0.0291). Displays of information on key performance indicators increase the odds of adequate routine health data use for decision making; respondents who reported that their organization displays information on key performance indicators were three (3) times more likely to have adequate routine health data use than those who did not display information on key performance indicators (OR=3.464[1.525–7.870], p=0.0030).

Discussion

This cross-sectional study examined the use of routine health data for decisions among primary healthcare managers and found that 63.30% of respondents used routine health data adequately. This could imply that some healthcare managers continue to make decisions without being informed by routine health data, which could impede realistic and proper health planning. One study conducted Tanzania reported that, data is collected for reporting purposes only, with little use of the information to inform decision making [13]. This study's findings are similar to those of studies conducted in Zanzibar-Tanzania and Ethiopia, which found that the level of routine health data use for decision making was 73.8% and 69.1%, respectively [15, 29]. Similarities in study findings could be attributed to a shared poor data demand and use culture, as well as inadequate health management information system infrastructures. Capacity building programmes and strong electronic health management information system infrastructures must be improved in order to increase data demand and use culture among health managers.

This study's findings shows that healthcare managers with less work experience (1 to 5 years) used routine health data for decision making more adequately than those with more work experience. This finding could be supported by the fact that in Tanzania, the adoption of web-based software packages for data management activities (DHIS2 and others such as GOTHOMICS, FFARS, eLMIS, and iMES) demanded experts to manage the systems. This created new job opportunities, with most of new employees having less work experience but more expertise in the field. Based on a study conducted in Tanzania, the main challenge confronting health management information system performance was limited human capacity to apply analytical tools and methods to synthesize information for decision-making [13]. Therefore, on job training to acquire skills in health data management and system operations is recommended for healthcare managers.

This study found that healthcare managers from Kondoa TC used routine health data for decision making more adequately than managers from Dodoma CC and Bahi DC. This could be explained by the presence of a few healthcare facilities that are easy to manage, the availability of data collection tools such as computers, and the availability of implementing partners who support data management issues, particularly on CTC, TB, and RCH. This finding could possibly be explained by the council management health team's (CHMT) constant supportive supervision. The geographical position of Dodoma CC and Bahi DC, on the other hand, poses challenges because facilities are widely spread in these districts, thus limiting adequate support from councils and implementing partners. Supportive supervision, according to Tilahun et al., could increase data quality and information utilisation by training healthcare managers in data management skills and decision-making capacity in their everyday activities [10].

When compared to dispensaries, healthcare managers from district hospitals and health centres used routine health data for decision making more adequately. This could be because district hospitals and health centres have more human resources, which leads to power separation, higher revenue collection, and good ICT infrastructure, facilitating for the installation of an electronic health information system, reliable internet connectivity, and easy accessibility of healthcare facilities, that grabs the introduction of donor-funded projects and more supportive supervision. This argument is supported by studies that found that the performance of higher level primary health care facilities may be due to the government's prioritizing of these facilities in terms of supervision and regular feedback [34, 35].

The usage of routine health data for decision making was associated with male gender. Because ICTs and other scientific studies are preferred more by males than females, this could imply that males use technology more than females, resulting in males becoming more proficient in executing health management information activities. This study's findings are comparable to those of an Ethiopian study, which found that male participants were more likely than female participants to use routine health data for decision making [32]. This implies that women should be empowered to manage routine health data in order to improve their performance in terms of data demand and usage for decision making.

The multivariate analysis revealed that, the strongest individual factors affecting adequate routine health data use for decision making were: making decisions based on healthcare needs, detecting outbreak, and comparing data to strategic objectives. In low-income countries with limited resources, effective decision making based on large population health requirements is crucial [30]. This could be useful for healthcare managers in tracking the progress of established health programmes and responding immediately if data shows a deviation from the set goal [13, 14]. According to MEASURE evaluation 2020, decision making based on information or evidence always results in correct and realistic decisions [12]. This finding concurs with one study, which found that experience and data do not always communicate the same information, which is why managers are encouraged to use data to make correct decisions rather than relying on their work experience [13]. This is also consistent with a study conducted in Kenya, which found that routine health data is critical in developing annual work plans, monitoring activities, and detecting outbreaks [36]. According to the literature, the availability of performance indicators display, such as performance graphical charts on notice boards or walls, quality improvement journals, staff meeting minutes, field feedback reports, and action plans, is an indication and evidence of facilities using routine health data generated [37].

Surprisingly, this study found that healthcare managers who reported using their superior directives and political interference for decision making used routine health data more adequately than their counterparts. This finding was unexpected, but it could be explained by the protective nature of workers who have to submit to their superiors in order to keep their job. This is in contrast to most of the literature, which reports that healthcare managers prefer to be empowered to oversee their programs and shift decision autonomy regarding health issues from political leaders to healthcare managers for improved results [38]. Failure to use data generated for decision making at primary healthcare facilities could result in the health system failing to fully link evidence to decisions and with less ability to respond to priority needs at all levels of the health system [39].

Another interesting finding was that, healthcare managers who claimed that a lack of equipment and qualified workers discouraged them from using routine health data for decision making used it more than their counterparts. In contrast, studies conducted in Malawi and Tanzania found that inadequate equipment, insufficient skilled personnel, and low motivation were among the factors that may influence HMIS underperformance in low and middle-income countries [40, 41]. The findings of this study might suggest that, the motivation to use data for decision making is within the person, which may result from understanding the significance of using routine health data for decision making despite the number of hurdles they encountered in their routine work.

This study found that healthcare managers who indicated that job promotion motivated them were more likely to have adequate routine health data use for decision making compared to healthcare managers who were not driven by job promotion. This could imply that healthcare institutions should build a working climate that encourages healthcare managers to have data demand and use culture for decision making, as well as hold themselves accountable when their decisions are not informed by routine health data. This is similar with th study conducted in Zanzibar-Tanzania which reported that, providing motivation such as incentives and job promotion to healthcare manager encourage healthcare manager to have adequate use of routine health data hence this would improve RHIS performance in primary health care facilities [15] .The government and implementing partners should encourage healthcare managers to use routine health data and offers incentives that are sustainable and cost-effective for the government, especially after the donor-funded project is phased down [10, 15].

This study found that healthcare managers who could check data accuracy, plot information by months, calculate percentages, explain findings and their implications, and use information to identify gaps had adequate routine health data use for decision making compared to their counterparts. This could imply that, healthcare managers had been capacitated to acquire skills in performing HMIS functions. Continued capacity building and advocacy programs on HMIS activities are critical for healthcare managers to have the necessary skills on checking the quality of data used, interpreting, presenting, and disseminating the correct results, which can lead to correct and realistic decision making. The findings of this study concur with those study conducted in Ethiopia, which found that healthcare managers who are competent in checking data accuracy and interpreting results have a positive impact on the performance of health management information systems [35]. Regular supportive supervision, according to [42, 43] should be emphasized more because it is a strong mechanism for feedback, capacity building, and mentorship for healthcare managers on HMIS activities in order to improve data quality and use for decision making.

This study exposed that healthcare managers who reported receiving organizational support used routine health data for decision making more adequately than those who did not. This implies that organizations possess the ability to promote or hinder the data demand and use culture to employees thus, in order to improve evidence-based decision making and HMIS performance, organizations should support effectively communicate to employees the issue of routine health data use for decision making. Studies have shown that, when organizational support is in place to support a culture of data-informed decision making, health care managers recognize the value of data use in the health system, and thus data is well communicated and shared within the organization for decision making [14, 44]. Similar findings were reported in Muhindo and Joloba's study, which found that organization support for routine health data use for decision making contributes to data/information ownership, resulting to an improvement in quality services to clients and, as a result, public satisfaction with health care services [23]. Therefore, regular supportive supervision of primary health care facilities is critical to foster data demand and a decision-making culture among healthcare managers.

This study's findings shows that, healthcare managers who reported regularly analysing data had adequate routine health data use for decision making when compared to their counterparts. This could be explained in terms of skills and equipment availability for performing HMIS activities, with those who did not analyse data on a regular basis most likely lacking data analysis skills and equipment. This argument is supported by the findings of this study, which found that approximately 27% of healthcare managers did not have access to a computer, 45% did not have access to the internet, 80% were demotivated by poor internet connectivity, 79% were demotivated by insufficient working tools, and 82% were demotivated by a lack of skilled personnel. Therefore, in order to increase the level of data use for decision making in primary healthcare facilities, the government must now hire experts with data analysis and management skills and equip the facilities with sufficient working equipment to improve RHMIS performance. Studies have shown that, most healthcare facilities lack health information technicians who are competent to perform various HMIS activities such as data analysis, so they fail to analyse their routine health data collected on a regular basis and use it for decision making [10, 29, 35].

Regarding the display of information on key performance indicators, this study found that healthcare managers who reported displaying their information on key performance indicators used routine health data for decision making more adequately than their counterparts. Displaying data on key performance indicators would assist healthcare managers in identifying disparities in service delivery that require further improvement [29]. This study's findings are consistent with other studies which found that, those who displayed performance data were more likely to use routine health data for decision making than those who did not [29, 45]. Health care facilities must build a culture of displaying information based on key performance indicators to support adequate routine health data use and the long-term sustainability of community health activities. Because of the presence of transparency and community ownership, this promotes confidence in using routine health data for decision making.

Strength and limitation of the study

This study adopted a validated questionnaire from the Performance of Routine Information System Management (PRISM) assessment tool, so the results are reliable. Given that the study was cross-sectional with a quantitative approach, there could be recall bias issues where respondents are more likely to provide answers that they believe the researcher will consider appropriate, that can lead to social desirability of their routine performance and availability of resources. This could have been addressed by cross-validating quantitative responses interviews with focus group discussions to gain a thorough understanding of how healthcare managers use routine health data for decision making. The design limits the study from making any casual inferences in relation to routine health data use for decision making in independent variable. This may have influenced the outcome of routine health data use for decision making when compared to the reported availability of working equipment, internet, skilled personnel, and trainings. Although proportionate sampling at the dispensary level yields less precise estimates of smaller groups, it yields better overall population estimates.

Conclusion and recommendation

The use of routine health data for making decisions was limited. It showed that male respondents with less experience (1–5 years) use available data to make decisions. Individual level factors (comparison of data with strategic objectives, decision based on health needs, and decision based on outbreak detection), technical factors (ability to check data accuracy, plot information by months, and explain findings and their implications), and organizational factors (organizational support, data analysis on a regular basis, and display of information on key performance indicators) were found to be associated with adequate routine health data use for decision making. Strengthening capacity, introducing motivation, supportive supervision, and adequate equipment to healthcare managers are critical for creating data demand and use culture, and thus overall health system performance.

Abbreviations

RHI	Routine Health Information
HMIS	Health Management Information System
PHC	Primary Healthcare

Supplementary Information

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Supplementary Material 1.

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Authors' contributions
FY, JN and NG developed and wrote the manuscript. FY involved in conducting the study and write manuscript. NG, JN and AK were involved in guiding the study design and reviewing the final manuscript. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
The University of Dodoma (UDOM) ethical clearance committee granted this study ethical approval at its 56th meeting on June 8, 2022 (Ref. No. MA.84/261/02). Permission was obtained from the Presidents' Office Regional Administrative and Local Government (PO-RALG) and each participating council. All methods were carried out in accordance with applicable guidelines and regulations. In addition, all subjects provided informed consent.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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