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Original Research Article

Determinants of data-driven decision-making among health providers: a case of Mombasa county, Kenya

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ABSTRACT

Background: Healthcare professionals understand how important it is to turn health data into information for informed decision-making. However, a lack of trustworthy and up-to-date health information is caused by inadequate investment in infrastructure for data collection, analysis, dissemination, and use. The aim of the study was to determine data-driven decision-making among health providers, a case of Mombasa County, Kenya.
Methods: The study employed an analytical cross-sectional study design where a stratified random sampling approach was utilized to recruit respondents into the study. The Yamane formula of sample size calculation was used to recruit 168 study partakers for this study.
Results: The outcomes indicated that quality data-driven decision-making exhibited a substantial correlation with technical factors (r=0.642, p value=0.000). Furthermore, the findings highlighted a significant correlation between quality data-driven decision-making and behavioral factors (r=0.821, p value=0.000). Additionally, the study's results revealed a marked correlation between quality data-propelled decision-making alongside organizational factors (r=0.819, p value=0.000).
Conclusions: The likelihood ratio tests demonstrated that both technical and organizational factors significantly predicted data-driven decision-making among health providers, whereas behavioral factors did not have a statistically significant impact. There is a need to provide training for health workers at the county level to enhance data utilization skills, ensure thorough data verification before submission, and promote the use of health information in decision-making.

Keywords: Health care providers, Health information management, Data-driven decision making

INTRODUCTION

A functional healthcare system necessitates data utilization across all levels, spanning from individual providers to sub-national and national health management teams. This approach aids in making evidence-based adjustments for enhanced quality of care.[1] The healthcare sector faces the challenge of improving access, cost-effectiveness, and quality amidst changing reimbursement models and regulations.[2] Quality data availability empowers managers to make informed decisions, while poor data quality can impede decision-making, negatively impacting organizational performance.[3] Healthcare professionals recognize the value of converting health data into info for sound decision-making.[4] However, inadequate investment in collecting analyzing, disseminating, and using infrastructure results in a lack of reliable and timely health information.[5] As a consequence, decision-makers struggle to identify issues, monitor progress, evaluate intervention impacts, and make evidence-based decisions on health policies, resource allocation, and program design. Evaluating data quality and information use practices is crucial to addressing this challenge.[6] Studies show that fewer than 50% of mid-level health managers possess the ability to analyze and use HMIS data.[4]

Although hospitals are recognizing the advantages of data-driven approaches for improvement, the healthcare sector lags behind other industries. Many healthcare programs in Kenya possess the capability to extract valuable information, conduct detailed analyses, and uncover new opportunities.[7] Essential elements such as patient details, medical products, purchases, and employee records have become integral for daily operations in local health facilities.[8] Decision-making decentralization county-wise creates a distinctive opportunity to advocate for data utilization closer to the delivery of service. All 47 counties underwent a three-phase process led by development partners to enhance data ownership and quality.[9]

Data flows from health volunteers within the community at health facilities and household level, aggregated in the health information system for analysis. The insights are subsequently conveyed to the community, health facility, and county levels to be acted on. In Kenya, health facility data are submitted to higher levels in the health system, implying data collectors aren't the final users at the facility level.[5] Health information utilization facilitates healthcare worker mobility for community dialogues and outreach, enhancing patient access to healthcare.[1] This communication fosters efficient stakeholder interaction, enhancing service delivery.

In their research, inadequate incentives and motivation for information use among healthcare managers, low adherence to HMIS rules, and insufficient technologies for data utilization.[10] Mombasa County's reliance on HIS reports for monitoring and evaluation exposes challenges, including incomplete, underutilized data and unknown factors influencing information utilization.[5] These issues drove the need to explore how technical, behavioral, and organizational factors, influenced by government policies, impact data-driven decision-making among health providers in Mombasa County. The aim of the study was to determine data-driven decision-making among healthcare providers in Mombasa County, Kenya.

METHODS

Study design

The analytical cross-sectional design facilitated the inquiry into the correlation between exogenous variables (technical, organizational, alongside behavioral factors) and the outcome of data-driven decision-making (dependent variable).

Study area

The study was situated in Mombasa County, encompassing 4 distinct sub-counties: Jomvu/ Changamwe, Nyali/Kisaun, Mvita, and Likoni. The evaluation of technical factors, behavioral factors, and organizational factors was conducted across the entirety of the 43 health facilities within Mombasa County.

Sampling technique

This study employed a stratified random sampling approach, this study methodically identified pertinent participants spanning the diverse categories comprising the overarching target population. Proportionate sampling was employed to select study respondents from the following subset of the population; county health management team, sub-county health management team, facility in charge, and head of departments.

Data collection

In this study, primary data was acquired via meticulously devised questionnaires to elicit information on the crucial variables of interest from the designated participants. The questionnaire comprised structured queries, employing a 5-point Likert scale. The study was carried out between September 2022 to August 2023.

Data analysis

Given that the primary data formed the bedrock of this study, quantitative data was subjected to scrutiny through descriptive statistics (standard deviation and mean) as well as inferential statistics (multinomial logistic regression analysis and Pearson correlation examination). The SPSS version 27 was employed to perform these analyses. The outcomes were elucidated using tables, chosen for their capabilities of facilitating comparison and enhancing interpretability. The nexus between dependent and independent variables was probed via Pearson correlation analysis. Statistical significance was set at a $p \leq 0.05$.

Ethical consideration

Prior ethical approvals were secured from the Institutional Ethical Review Committee (IREC) at MKU, and a study permit was duly acquired from NACOSTI. Ensuring the highest degree of confidentiality, data gathered from study participants were handled with the utmost discretion. Study participation was wholly voluntary, further underscoring commitment to ethical principles.

RESULTS

Demographic characteristics

The outcomes revealed that 109 individuals (65%) were below the age of 40, 54 respondents (32%) belonged to the clinician cadre, 60 participants (35.7%) held degrees, 60 individuals (35.7%) had accumulated over 4 years of employment, and 58 respondents (34.5%) were associated with the OPD section. The demographic findings are presented in Table 1.

Data-driven decision making

As indicated in Table 2, This section provides descriptive insights into the dependent variable, focusing on decision-making propelled by data. The mean score for the statement emphasizing the prominence of data completeness for decision-making was 4.19. Around 63.5% of respondents expressed that data completeness is crucial for effective decision-making. Similarly, 82.5% highlighted the significance of data consistency in the decision-making process. Furthermore, 68.1% indicated that the submitted data encompasses all requisite dataset reports. Regarding the assertion about taking prompt corrective actions to address data reporting issues, 39.8% agreed, while 41.5% maintained a neutral standpoint. In contrast, 6.7% disagreed with this statement. For the statement concerning the existence of procedures for data distribution and reporting, 50.3% concurred, whereas 42.1% maintained a neutral stance, and 6.7% disagreed. Notably, 89.9% acknowledged the presence of criteria for verifying the completeness and consistency of collected data.

Technical factors and data-driven decision making

Table 3 summarizes the subjects' agreement level regarding how technical variables influenced quality data used in decision-making within Mombasa County. From this study, a significant respondent majority, comprising 96.2%, acknowledged that the existence of technically qualified human resources is pivotal in backing effective data management. Similarly, 96.1% of the participants concurred that the development of skills in analyzing, interpreting, and decision-making is essential in facilitating the use of information. A notable 87.4% of respondents affirmed that health providers prioritize patient care over data collection, and 83.3% expressed that decentralizing RHIS management could improve the local utilization of health information data. Moreover, 83.9% of the respondents agreed that training in data management at the facilities level could foster the use of high-quality data in processes of decision-making. Additionally, 79.1% of the participants indicated that technical determinant factors are connected to specialized expertise in quality data management.

Behavioral factors and data-driven decision making

Table 4 provides a summarized representation of respondents' agreement levels concerning the impact of behavioral aspects on the use of quality data in making decisions within Mombasa County. Notably, 93.3% of participants acknowledged that the perceptions and attitudes of senior management towards data significantly impact the utilization of health information. The majority of respondents, accounting for 95.4%, concurred that a positive attitude prevails toward data collection and usage. Additionally, 85.7% expressed that perceptions of HIS processes and associated tasks contribute to improved quality data-driven decision-making. A significant proportion of 73.5% indicated that managers of health facilities often gather data devoid of comprehending their utilities. Moreover, 63% of respondents revealed that the absence of incentives for data gathering affects the quality of data-driven decision-making, while 71.5% agreed that reinforcing health workers' sense of data ownership is necessary.

Organizational factors and data-driven decision making

Table 5 provides a summarized overview of respondents' agreement levels regarding the organizational factors' effects on quality data-led decision-making within Mombasa County. An overwhelming majority of respondents, comprising 95.8%, indicated the presence of structures and processes designed to enhance collaboration between data users and producers. Furthermore, 93.4% agreed that roles and responsibilities relating to data usage for informed decision-making are well-defined. In addition, 81.9% concurred that recognition and reward systems are established for commendable data system performance. A considerable percentage of 57.1% affirmed the sharing of best practices in Health Information System (HIS) utilization. Moreover, 75.3% expressed the availability of sufficient resource allocation for support supervision of data systems, and 89.9% acknowledged the existence of feedback mechanisms for health information data utilization.

Correlation analysis between organizational, technical, behavioral factors and data-driven decision-making

The researcher conducted a correlation examination to establish the potential relationships among the variables. Pearson correlation was employed for this analysis, utilizing the (r) coefficient to assess the linear connection between the study variables. The correlation coefficient generates a statistic spanning from negative (denoting ideal negative correlation) to 1.0 (reflecting ideal positive correlation), offering insights into the strength of the connection between 2 variables.11 The magnitude of the coefficient of correlation value indicates the robustness of the association between these variables. A value of zero for (r) signifies the absence of any connection between the variables. The computation of correlation coefficients was undertaken for each pair of variables, with the outcomes tabulated in the correlation matrix as indicated in Table 6.

The outcomes indicated that quality data-driven decision-making exhibited a substantial correlation with technical factors ($r=0.642$, $p=0.000$). This observation signifies that positive alterations in technical factors were linked with enhanced quality data-driven decision-making. Furthermore, the findings highlighted a significant correlation between quality data-driven decision-making and behavioral factors ($r=0.821$, $p=0.000$).

This underscores the notion that favorable shifts in behavioral factors were associated with heightened data-led decision-making. Additionally, the study's results revealed a marked correlation between quality data-propelled decision-making alongside organizational factors ($r=0.819$, $p=0.000$). This indicates that favorable modifications in organizational factors were linked to improved quality data-driven decision-making.

Multinimomial logistic regression between study variables

As indicated in Table 7, The outcomes encompass likelihood ratio tests that evaluate the combined impact of each exogenous variable on the model (when a variable becomes introduced as a factor, its outcome signifies an overall test of that factor). Applying the conventional threshold of p=0.05, both technical factors and organizational factors remained significant statistically with p<0.05, signifying their significance as predictors within the model.

Hence, they stand as the primary determinants of quality data-driven decision-making among health providers in Mombasa County. However, behavioral factors exhibited statistical insignificance with p>0.05.

Table 1: Demographic information.

Characteristics		N	%
Age of respondents (years)	20-30	63	38
	30-40	46	27
	40-50	28	16.5
	>50	31	18.5
Respondents' Ccadre	Clinicians	54	32
	HRIO	36	21
	MLO	18	11
	NURSE	32	19
	Pharm/Tech	28	17
Respondents' education level	Certificate	25	14.9
	Diploma	49	29.2
	Degree	60	35.7
	Postgraduate	34	20.2
Respondents' employment duration (years)	<1	21	12.5
	1-2	36	21.4
	3-4	51	30.4
	>4	60	35.7
Respondents' section of work	OPD general	58	34.5
	MCH	43	25.6
	Special clinic	26	15.5
	LAB	21	12.5
	HMIS	20	11.9

Table 2: Data-driven decision making.

Statements	1	2	3	4	5	Mean	SD
	%	%	%	%	%		
Completeness of reported data is essential for decision-making	0.4	14.4	21.8	38.9	24.6	3.73	1.00
Consistency is essential for decision making	0.0	1.1	16.5	35.1	47 .4		
Reported data includes all the necessary dataset reports	0.4	2.8	28.8	33.0	35.1	4.00	0.89
Corrective actions are always taken within reasonable address data reporting issues	1.1	17.6	41.5	35.6	4.2	3.24	0.83
There is a procedure for distributing and reporting data	0.7	6.7	42. 1	44.2	6.3	3.49	0.74
There is criteria for verification of completeness and consistency of data collected	0.0	0.3	9.8	59.6	30.3	4.20	0.61

Table 3: Technical factors and data-driven decision-making.

Statements	1	2	3	4	5	Mean	SD
	%	%	%	%	%		
Availability of technically qualified human resource is key in supporting data management	0.0	0.0	3.8	65.2	31.0	4.27	0.52
Developing skills in analyzing, interpreting and decision-making promote information use	0.0	0.0	3.8	67.9	28.2	4.24	0.51
Health providers value the care of patients over data	0.0	0.0	12.6	49.8	37.6	4.42	3.02
Routine health information systems management should be decentralized to improve local use of health information data	0.0	0.0	16.7	34.5	48.8	4.32	0.74
Training in data management at facility level may promote good quality data to be used in decision making processes	0.0	0.0	16.1	43.9	40.0	4.24	0.7 1
Technical determinant factors are related to the specialized know-how on quality data management	0.0	0.0	20.9	39.7	39.4	4.18	0.76

Table 4: Behavioral factors and data-driven decision-making.

Statements	1	2	3	4	5	Mean	SD
	%	%	%	%	%		
Perceptions and attitudes of senior management towards data have an influence on the use of health information	0.0	0.0	6.6	68.3	25.1	4.18	0.53
There is a positive attitude towards data collection and use	0.0	0.0	4.5	70.7	24.7	4.20	0.50
Perception on HIS processes and related tasks unproves quality data driven decision making	0.0	0.0	14.3	68.2	17.5	4 03	0.56
Health facility managers gather data without understanding its utility	0.0	0.0	18.5	37.3	36.2	4.10	0.79
Quality data-driven decision-making is affected by a lack of incentives for data collection	0.0	0.7	36.4	42.7	20.3	3.83	0.75
There is a need to strengthen health workers' sense of data ownership	0.0	0.0	28.6	29.3	42.2	4.14	0.83

Table 5: Organizational factors and data-driven decision-making.

Statements	1	2	3	4	5	Mean	SD
	%	%	%	%	%		
There are feedback mechanisms on health information data utilization	0.0	0.3	9.8	59.6	30.3	4.20	0.61
We have structures and processes for improving the interaction of data users and producers	0.0	0.3	3.8	69.7	26.1	4.22	0.52
We define roles and responsibilities related to using decision making	0.0	0.0	6.6	51.6	41.8	4.35	0.60
There are recognition and reward systems for good performance of data systems	0.0	0.0	18.1	33.8	48.1	4.30	0.76
There is sharing of best practices on HIS utilization on data system	0.0	1.0	41.8	33.4	23.7	3.80	0.81

Table 6: Correlation analysis results for study variables.

		Y	X1	X2	X3	M
Y	Pearson correlation	1				
	Sig. (2-tai1ed)					
	N	168				
X1	Pearson correlation	0.642**	1			
	Sig. (2-tai1ed)	0.000				
	N	168	168			
X2	Pearson correlation	0.821**	0.614**	1		
	Sig. (2-tai1ed)	0.000	0.000			
	N	168	168	168		
X3	Pearson correlation	0.819**	0.555**	00.880**	1	
	Sig. (2-tai1ed)	0.000	00.000	00.000		
	N	168	168	168	168	
M	Pearson correlation	0.563'*	00.410"	0.491"	0.521"	1
	Sig. (2-tai1ed)	0.000	0.000	0.000	0.000	
	N	168	168	168	168	168

Note: **-Correlation remains significant at 0.01 level (2-tailed). Key; Y= Data-driven decision making; X1= technical factors; X2= behavioural factors; X3= organizational factors; MW overnment Policy.

Table 7: Multinimomial logistic regression.

Effects	Model fitting criteria		Likelihood ratio tests			
	AIC of reduced model	**BIC of reduced model**	**-2 log likelihood of reduced model**	**Chi-square**	**df**	**Sig**
Intercept	394.098	506.561	322.098	47.192	12	0.000
Technical factors	395.371	507.833	323.371	48.465	12	0.000
Behavioral factors	364.542	477.005	292.542	17.636	12	0.127
Organizational factors	367.614	480.076	295.614	20.7	12	0.055

Note: The Chi-square statistic represents the disparity in 02 log likelihoods between the ultimate model and a simplified model. The simplified model is created by excluding an effect from the ultimate model. The null hypothesis posits that all parameters of that effect are equal to 0.

DISCUSSION

Concerning data-driven decision-making, These findings resonate with those of a study done in Kenya where they identified data quality across four dimensions: completeness, accuracy, and consistency, alongside timeliness.[12] Completeness pertains to not solely the proper completion of all data facets in report forms of the facilities, but also to the percentage of facilities submitting reports within a given area of administration like a district. Timeliness evaluates whether reports are submitted according to established deadlines.[13] further emphasized that data accuracy is evaluated through comparisons between reports and records of facilities, as well as between facility databases and reports within administrative areas. The concept of consistency addresses the level of correspondence between patient data on patient cards alongside registers. Timeliness, meanwhile, assesses if health facilities adhere to the specified schedule for reporting to higher administrative levels.

From this study, organization factors were statistically associated with data-driven decision-making. These findings align with those of research done in Kenya where the presence of organizational systems supporting a data-led decision-making culture, results in enhanced data quality, and improved communication and sharing of data throughout the health system, ultimately leading to its effective utilization in decision-making.[5] Conversely, the absence of consistent systems for Monitoring and Evaluation activities undesirably influences the supposed significance and quality of data gathering and usage. Transforming an organization into an information-oriented culture poses challenges, necessitating sustained behavioral interventions over the long term.[14,15] Similarly concluded that missing mechanisms for feedback deprive sub-counties of the opportunity to employ HI for service enhancement. The generated information should benefit healthcare management and facilities by providing them with feedback for informed decision-making. In their study, though reports' submission is done to the MOH, no established measures guarantee that the info from these reports remains relayed back to the submitting facilities, thus emphasizing the significance of feedback to complete the data reporting cycle. The availability of feedback notably influences how health facilities utilize health information to inform their decisions.[16]

From this research, technical factors were statistically associated with data-driven decision-making. The outcomes aligned with those of a study carried out in Kenya which highlighted the association between technical determinant factors and specific know-how required in developing, managing, and enhancing HIS performance and processes.[17] From their research, they asserted that under the PRISM framework, irrelevant indicators, complex data collection forms, and user-unfriendly computer software can undermine HIS implementers' motivation and confidence.[18] Equally, inadequate data processing by software can lead to ineffective analysis and hinder significant conclusions for decision-making, consequently impacting information use.[19] Furthermore, the outcomes of this study align with those of a study done in India, which underscores that enhancing skills in analyzing, and interpreting, as well as decision-making encourages information use.[20] In their study, they revealed that a properly designed HMIS, coupled with appropriate training following internationally recognized practices, contributes to the data quality necessary for informed decisions.[21]

Concerning behavioral factors, the results from this study aligned with, who in their study unveiled the detrimental impact of insufficient incentives for data gathering and the limited understanding of data utilities on HIS performance.[13] The results further underscore that managers frequently fail to integrate the generated information into their managerial activities, a behavior that ultimately influences the utilization of health information. Consequently, comprehending collective values linked to HIS processes and related tasks is crucial for promoting values that foster the utilization of Routine -HIS (RHIS). This, in turn, can augment the efficacy of health information utilization in the processes of making decisions.

Furthermore, such outcomes are consistent with those of a study carried out in Ethiopia, which asserted, that perceptions as well as attitudes of senior management towards data significantly shape the utilization of HI.[22] When senior management does not prioritize evidence-based decision-making alongside information utilization for transparency and accountability, it becomes unlikely that an information-oriented culture will be cultivated. In their study, they emphasized the importance of scrutinizing the values, attitudes, and perceptions of senior management and additional organizational employees regarding information-centric functions.[23] To enhance HI utilization in developing nations, it is imperative to strengthen the sense of data ownership among health workers and eradicate the discernment that their role concludes with data collection and transmission.[13]

CONCLUSION

From the outcomes of this investigation, the researcher arrived at the determination of the existence of a constructive and robust association between technical variables and the practice of data-driven decision-making within the health provider domain. Specifically, the study found that technically adept human resources availability plays a pivotal role in bolstering data management among health providers. Furthermore, the cultivation of skills in analysis, interpretation, and decision-making contributes significantly to the utilization of information. Furthermore, the study's results culminated in researchers concluding that a substantial and positive correlation exists between behavioral factors and the caliber of data-driven decision-making executed by health providers. Notably, behavioral determinants such as the demand of HIS users, their competence, motivation, and confidence in HIS activities directly influence performance and HIS processes**.** Based on the empirical evidence, the study confirmed a substantial and affirmative relationship between organizational factors and the practice of data-driven decision-making within the realm of health workers operating in Mombasa County. Concretely, the study deduced that a facility that establishes processes and structures to enhance interaction between data producers and users offers lucid guidelines for maintaining data quality, and demarcates responsibilities and roles tied to data usage can serve to fortify other interventions directed at advancing data-informed decision-making.

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