Factors Influencing Utilization of Health Data for Decision Making by Community Members in Nyando Sub-County, Kenya

Henry Kilonzo[1*], Dr. Doreen Othero[1], Dr. Benard Guyah[2]

[1]Department of Public Health, Maseno University

[2]Department of Biomedical Sciences and Technology, Maseno University

***Corresponding author**

DOI: https://doi.org/10.51244/IJRSI.2025.1215000116P

Received: 20 July 2025; Accepted: 26 July 2025; Published: 26 August 2025

ABSTRACT

Utilization of health data is key because it enables individuals and communities to make decisions on their health seeking behaviour. However, studies show low utilization of health data for this purpose. In Kenya, majority of health programs provide feedback on health data to communities through conventional methods such as health talks in health facilities, use of mass media, posters and billboards. Despite these, less than 38% of health data is used for decision making. This can be attributed to the ineffective methods of providing feedback to communities. This study therefore investigated the factors influencing utilization of health data for decision making among community members. It was a longitudinal interventional (pre-post) study for 12 months. 440 participants were sampled using Yamane's formula. Quantitative data was collected using semi-structured questionnaires while qualitative data was collected through Focus Group Discussions and Key Informants Interviews. Quantitative data was analyzed using SPSS version 25 and R. Qualitative data was analyzed using the NVivo application. Utilization of health data for decision making at baseline showed that use of prevention of malaria data was at 187 (42.5%), TB prevention at 188 (42.7%), HIV/AIDS prevention 210 (47.8%), ANC 123 (28%), Deworming 146 (33.2%), Child Immunization 156 (35.5%) and hygiene and sanitation was at 117 (26.6%). Findings from the qualitative survey resonated with these results. The main factors that influenced utilization of health data for decision making were; Education Level, for HIV data use (P=0.01, OR=2.5); Age, for malaria data use (p=0.07, OR=2.05); Education Level, for TB management data use (P=0.00, OR=2.3); Religion, for ANC data use (P=0.02, OR 2.2); and Gender, for child immunization data use (p=0.03, OR=1.7). The key factors found to influence utilization of health data included: Age, education level, religion and number of children per household.

Keywords: Health, Data, Utilization, Decision Making, Community

INTRODUCTION

Utilization of health data is key because it enables individuals and communities to make decisions on their health seeking behavior (Tilahun et al., 2021)[1]. Consistent use of health data for decision making has the potential benefits of helping healthcare providers to engage communities in interventions that improve their health status while empowering individuals and communities with health-related information (Tilahun et al., 2021)[1]. However, data generated in the healthcare systems in Low- and Middle-Income Countries often go under-utilized, remaining confined to reports and shelves UNICEF, 2024)[2]. Studies show low utilization of health data for decision making in South Africa at 65%, and Cote D'Ivoire at 57.4% (Nutley et al., 2019[3]; Thawer, S., et al, 2022)[4]. In Kenya, only 38% of health data is utilized for decision making at community level (Yarinbab & Assefa, 2018)[5] hence slow progress in the improvement of key health indicators. Overall, the low utilization of health data has led to compromised quality of healthcare and limited ability to attain health goals. This can be attributed to the ineffective methods of providing feedback to communities resulting in poor health problem identification.

Traditional health education strategies are often distributed through healthcare organizations and mass media that may not constantly be effective (Sally et al.,2006)[5]. In Kenya, majority of health programs provide feedback on health data to communities through conventional methods such as health talks in health facilities, use of mass media, posters and billboards. On the centrally, Behavior Change Interventions (BCIs) offer a comprehensive approach to health communication by actively engaging individuals, tailoring messages to cultural contexts, facilitating interactive feedback, reinforcing behaviors, and empowering individuals through enhanced self-efficacy. These strategies have demonstrated superior effectiveness in improving the utilization of health data for decision-making at the household level compared to conventional communication methods (Anees Alyafei and Raul 2024[6]; Ritchie D, Van den Broucke S, Van Hal G, 2021[7]).

Health data use is important in bridging the gap in what is known and what is done (the Know-Do-Gap) in community health service delivery. Encouraging data use for decision making at the community level including outreaches, door step strategies for child survival, HIV/AIDS and family planning related interventions promote accountability of local health system and community priorities (Bjorkman, 2009[8]).

A study in Tanzania revealed limited utilization of data, where it was primarily gathered for reporting rather than to support decision-making (Mboera et al., 2021[9]). Similarly, in Kenya, 43% of health data producers lack the necessary skills to analyze and interpret data, while only 42% of health facility managers possess the capacity to analyze and apply data to inform communities about their health needs and contribute to the budgeting and planning of clinical services (Scientific Symposium Report, 2020). It is equally worth noting that in Kenya, only 38% of collected data is analyzed and used for decision making (Ministry of Health, 2020). The under-utilization of health data contributes to data often stored as reports and in databases; hence not adequately utilized to inform health programming at community level (Nutley, 2014[10] and Mboera et al., 2021[9]).

Rexhepi (2019[11]) highlights that the complexity involved in the design of data entry and recording systems is the most significant technical challenge impacting the use of routine health data in public health facilities. Similarly, Hossain (2012)[12] emphasizes that the complexity of such systems often discourages health workers from using them, leading many to revert to manual, paper-based records. This practice frequently results in damaged or poorly managed data. According to Hossain (2012)[12], investing in comprehensive capacity building (both in digital infrastructure and human resources) across the health system proves to be more effective and cost-efficient. When such tools are combined with targeted training on data-driven decision-making, it fosters greater ownership, improved analysis, and increased use of data throughout the health system (Regeru et al., 2020)[13].

A study conducted in Uganda by Asiimwe (2018)[14] highlighted that community-related factors such as the lack of a strong information culture and inadequate quality supervision contributed to the limited use of health data in decision-making processes. In Kenya, the community health strategy 2020-2025 emphasizes the community-based approach as the mechanism through which communities and households play an active role in health and health-related development matters (MoH, 2020)[15]. It prioritizes community-based health information systems (CBHIS) as a tool to empower the community through collection and use of health data for decision making.

Factors such as education, gender, socioeconomic status, ethnicity, religion and religious beliefs, biological, psychological and personal history factors have been associated with decision making. The community members become more self - esteemed, confident, motivated and committed to participate in exploring solutions to their challenges (Marlize, 2000)[16]. As they become empowered, they also become better able to articulate their needs. This later perspective is further reinforced by Mukama (2003)[17] who observes that when the community is empowered, they are able to ask questions, seek improvement, learn, and improve the quality of health programmes.

Community health data provides a key first step in ensuring good quality services for all people (CHW Central, 2025)[18]. Access to healthcare is a human right which further entails the right to sound health information as a procedural right to its realization. The level of confidence among health data management teams can significantly impact how effectively routine health data is utilized to improve public health outcomes.

The Behaviour Change Interventions: Use of the DECIDE Model

The DECIDE model (D-Define problem; E-Establish criteria or factors to be considered; C-Consider

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XII Issue XV July 2025 | Special Issue on Public Health

alternatives; I-Identify the best choice; D-Develop action plan; E-Evaluate the performance) provides a structured framework for implementing Behaviour Change Interventions (BCIs). It is a six-step decision making process that guides practitioners through sequential steps to design, execute, and evaluate programs effectively. The model has not been attributed to a single author but builds on principles of rational decision making and the need for structured approaches to problem-solving. Here's how BCIs aimed at improving household utilization of health data can be implemented using the DECIDE Model (Fig. 1):

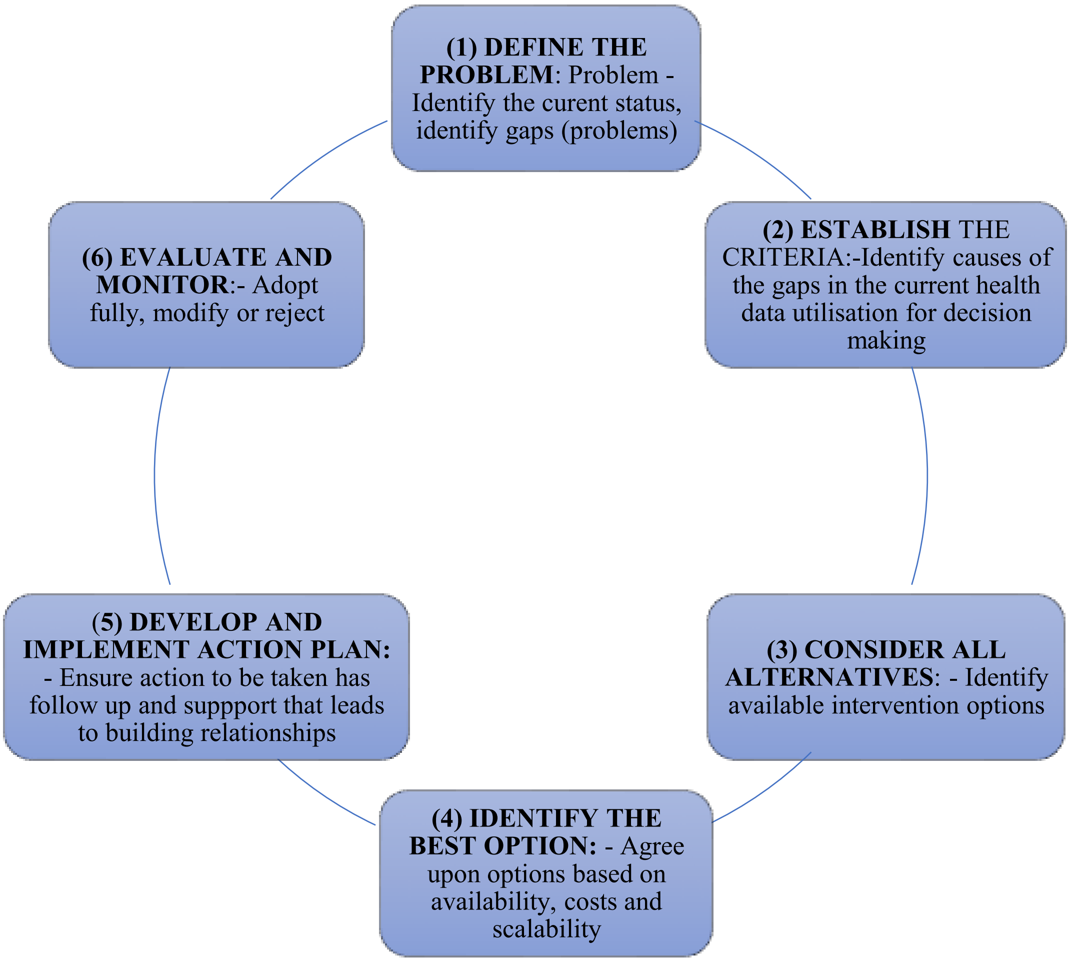

Fig 1: The DECIDE Model

Health data holds little value if it is not used to guide decisions. Utilizing health data for decision-making should be viewed as an ongoing, knowledge-based process rather than a one-time goal. This process demands the continuous collection, analysis, and dissemination of data to detect and respond to both positive and negative trends effectively.

Theoretical Framework

Two theories were selected for this study as most appropriate for anchoring theoretical concepts and interpreting findings. These are: the socio-Ecological Model (EM) and the Health Belief Model (HBM) and are described below.

Health Belief Model (HBM). The HBM is an individual-level behavior model with a long history in behavioral research in decision making and is suitable for explaining behaviors of healthy and asymptomatic individuals who engage in non-medical and medical activities (Rosenstock *et al*.1988)[20]. This model theorizes on people's beliefs regarding the risk of a health problem and their perceptions on the benefits of taking actions to avoid it, analyzes their readiness to take action. Additionally, individual factors such as age, gender, ethnicity, socioeconomic status, individual's awareness, cues of action, the benefits and ease of adopting a behavior can help to predict whether preventive measures were adopted.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XII Issue XV July 2025 | Special Issue on Public Health

The Socio-Ecological Model (EM) illustrates how myriad factors influence an individual health behavior. The model comprises five levels which include Individual, Interpersonal, organization, community and policy. These constructs provide a multidimensional approach to understanding and addressing factors associated with decision making on health seeking behaviours by individuals and households. Individual level factors relate to personal characteristics that influence behavior such as knowledge, attitudes, misconceptions and beliefs. The interpersonal level relates to how a person's behavior is influenced by his/her relationship with other people, such as family, friends, colleagues and peers (McLeroy et al., 1988)[21].

Conceptual framework of the study

The Behavior Change Intervention aimed at positively influencing the knowledge, attitudes and perceptions resulting in an increase in use of health data for decision making. The factors for investigation in this context included the independent variables which were the individual social demographic and health service factors; proximate variables that included the health and environmental data including safe water and sanitation, housing, water sources services sought by the community members; the behaviour change intervention; and the dependent variable.

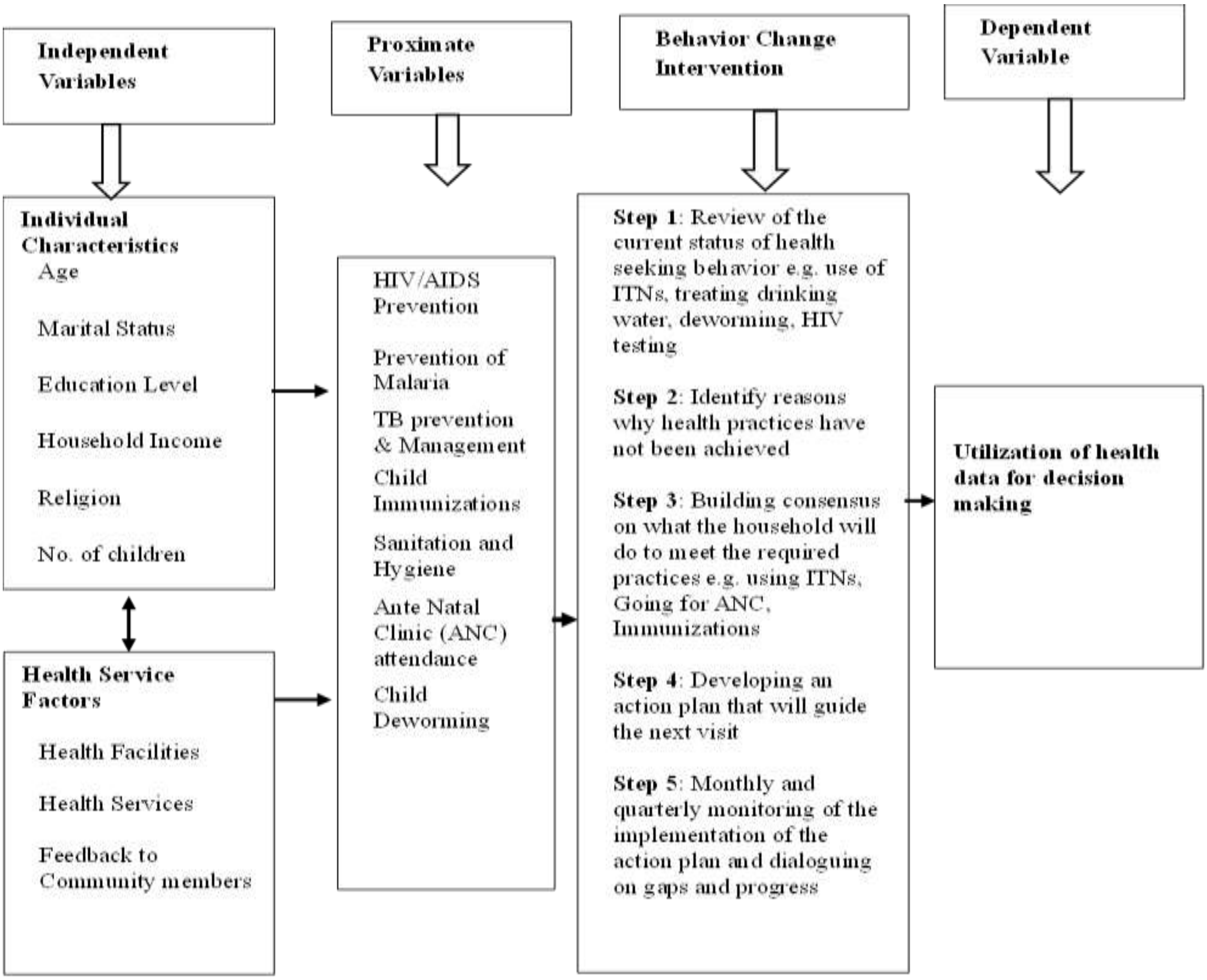

Figure 2: The Conceptual Framework (From reviewed Literature)

METHODS

Study Area

The study was conducted in Nyando Sub County, Kisumu County, Kenya which has a population of 161,508 domiciled in 77,121 households (KNBS, 2019)[22]. The seasonal flooding contributes to WASH and also disease

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XII Issue XV July 2025 | Special Issue on Public Health

outbreak challenges (National Water and Storage Authority, 2025)[23]. The Sub- County has high disease and social economic burden. Key health outcomes are poor and 60% of the population remains poor living below USD 1.9 per day (KDHS, 2023)[24]. It has a total of 46 health facilities representing 13% of the total number of facilities in Kisumu County; which are supported by 437 Community Health Promoters (Lab Flow, 2025)[25].

Study Design

This was a longitudinal interventional study (pre-post study) design adopting both the quantitative and qualitative approaches to data collection, analysis and presentation (Mugenda and Mugenda, 2003)[26]. The rationale for this choice was because it enables the capture of information based on data collected over a period of time and is useful for demonstrating temporal changes in a behavior of interest during and after the intervention period. The study was conducted in five phases over a period of 12 months for practical, logistical and operational efficiency between 1st December 2021 and 30th November 2022.

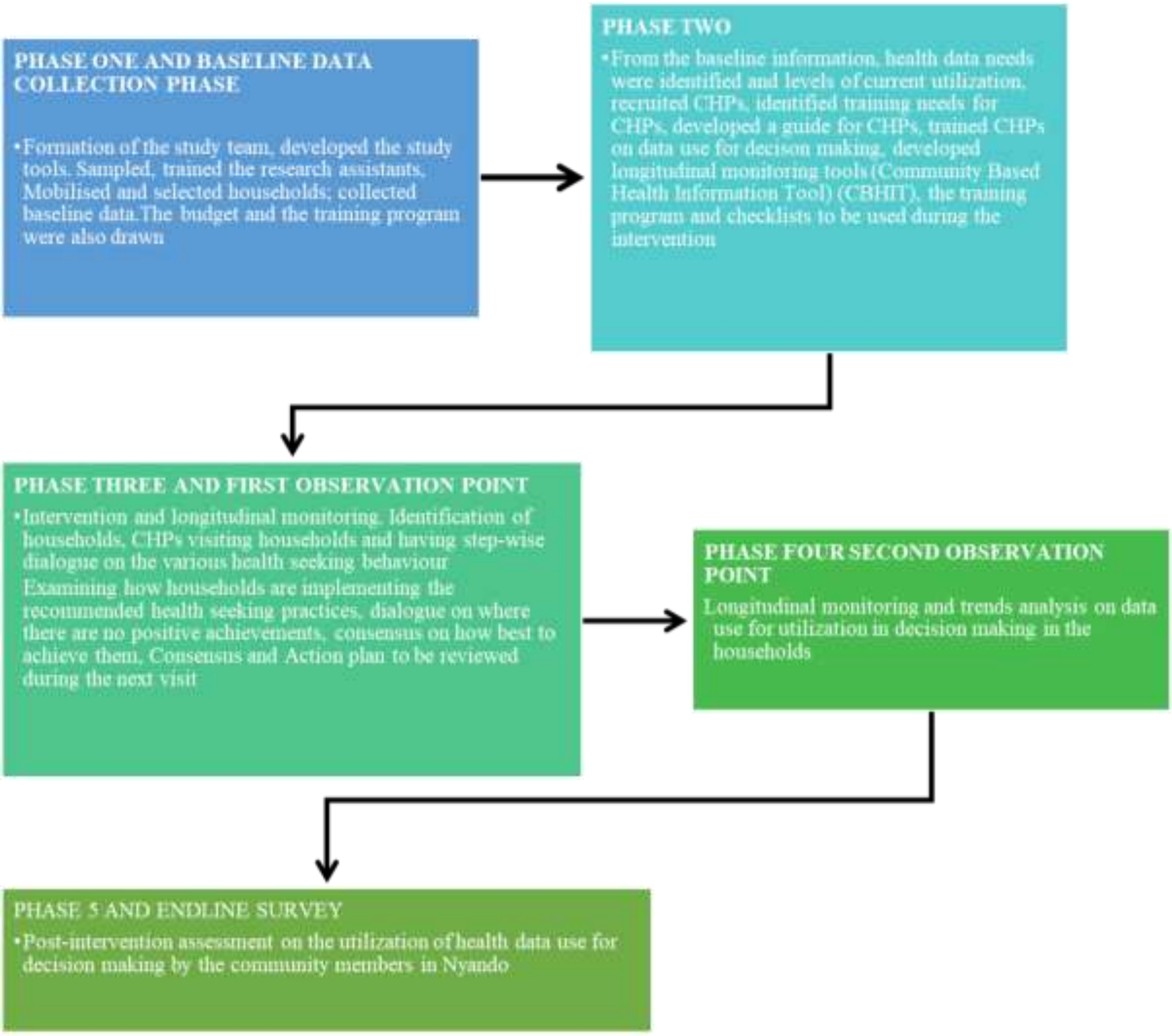

Figure 3.1: Flow chart of the Study Phases

Study Population

The target population: The target population comprised of the 77,121 heads households in Nyando Sub County (KPHC Vol III, 2019)[27] .

Inclusion Criteria

i) Nyando Sub County adults who were heads of households

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XII Issue XV July 2025 | Special Issue on Public Health

ii) Respondents were limited to Nyando Sub County residents who gave informed consent

iii) Residents who committed to stay continuously for at least one year in Nyando Sub County during the time of the study

Exclusion Criteria

1. Residents who had major disabling medical conditions at the time of the study hence were unable to cooperate

2. Those who declined to participate in the study at any stage during the study

Study Variables

Independent variables included socio-demographics such as age, gender, religion, marital status, level of education, household income, source of income or occupation.

Dependent variables of the study was the utilization of health data for decision making by communities in Nyando sub-county.

Sample Size Estimation

The sample size was determined from the target population of the 77,121 households in Nyando Sub County (KPHC Vol III,2019)[27]. Taro Yamane (1967)[28] equation was used in sample size estimation to get a representative sample size. Yamane's equation is ideal when the target population is known.

. $n = \frac{N}{1+N(e)^2}$

Where: n = Desired Sample size

N = Population size

e= Level of precision or sampling of error which is ±5%

$$n = \frac{77{,}121}{1+77{,}121 *(0.05*0.05)} = 399.5 = 400$$

To the estimated sample size, an additional 10% (40) was factored to take care non-response or drop-outs (Niang et al., 2006)[29]. Thus, a total of 440 respondents were enrolled for the study.

A total of six Key Informants for the study were selected through purposive sampling using a criteria. A total of 5 FGDs (one in each ward) were also held with the community groups during their quarterly dialogue meetings.

Sampling Procedure

For Quantitative Data Multi-stage sampling and Probability Proportionate to Size (PPS) sampling were adopted (Mugenda and Mugenda, 2003)[26] to select the Wards then to the sub locations, villages and finally at households respectively since the samples from Wards and Sub locations had different population sizes. For Qualitative Data, purposive sampling was used for the aforementioned KIIs.

Validity and Reliability

Instruments were pre-tested on 44 respondents (10%) from North Nyakach Ward (Neighboring with similar background characteristics. On Validity, the tools were aligned and examined by the Supervisors and experts and the research findings were enhanced by employing pretest findings to improve accuracy of the data collection

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XII Issue XV July 2025 | Special Issue on Public Health

tools. Behavior Change Intervention Guide captured inputs from 3 specialists (outside the research team) in health education and promotion (2 people) and a Biostastician (1 person). On reliability, a Test-retest approach was used were 10% of the sample size (44) was used to pre-test the tool. Cronbach Alpha test at an interval of one month obtained a correlation coefficient of 0.811 (above 0.7 which is the recommended) - (Nunnally, 1978)[30.]

Data collection

Quantitative data was collected using a questionnaire in two weeks at the baseline (before Behavior Change Intervention) and two weeks for end line using the same tools that were used before Behavior Change Intervention. qualitative Data was collected through six Key Informant interviews at the baseline and end line while five FGDs were also held with the members of households during the quarterly dialogue meetings in the designated meeting centres comprising 8-12 participants. Additional material was obtained from local and international journals, articles, books, newspapers and electronically stored data. Libraries in Maseno University and other institutions of higher learning were visited for more reference material.

Data management and statistical analysis

Quantitative data collected was analysed in SPSS version 23 and R programming for further data management, manipulation and analysis. Descriptive statistics including percentages, frequencies was used to analyse the demographic characteristics of the respondents. Bivariate analysis was carried out to establish the relationship between the utilization of health data for decision making with socio-demographic and health factors using chi-square test statistics. The covariates with Probability value less than 0.05 were further carried into the logistic regression to test the strength of the association between the utilization of the health data with the socio demographic and health factors. The qualitative data was analyzed using NVIVO 14 application for thematic analysis.

Ethical considerations

Ethical Approvals were obtained from Maseno School of Graduate Studies, Maseno University Ethics and Review Committee, National Commission for Science, Technology and Innovation and the Kisumu County government. Informed consent was obtained from all participants and the study data were stored in password protected computers and lockable cabinets which were accessed only by authorized researchers.

RESULTS

The Study Response Rate

A total of 440 participants were selected for the study per administrative Ward and a response rate of 100 % was attained as shown in Figure 3.

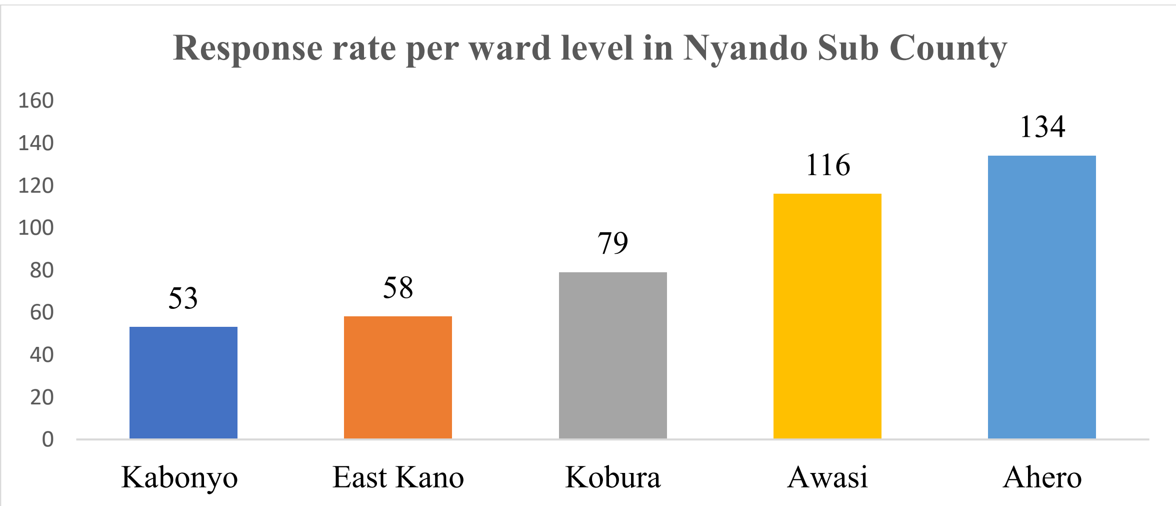

Figure 3: Response rate per ward level in Nyando Sub County

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XII Issue XV July 2025 | Special Issue on Public Health

Sociodemographic Characteristics of the Participants

Majority of the respondents were female (78.4%, n=345) and majority were aged between 31-40 years (35.5%, n=156). Most of the participants were married (95.5%, n=420) while majority of them reported to have attained primary education level (58.6%, n=258). In terms of participants' religion, majority were protestants (78.4%, n=345) and with at least four children (40.5%, n=178). The socio-demographic characteristics are illustrated in Table 1.

Table 1: Socio demographic Characteristics of the study respondents

Characteristics	**n=440**	**(%)**
Age 18-30	104	23.6
31-40	156	35.5
41-50	86	19.5
51 and Above	94	21.4
Gender		
Male	95	21.6
Female	345	78.4
Marital Status		
Married	420	95.5
Separated	8	1.8
Single	12	2.7
Education Level		
Primary	258	58.6
Under primary	21	4.8
Secondary	161	36.6
Religion		
Protestant	345	78.4
Catholic	95	21.6
Number of Children per household		
0-4	178	40.5
5	124	28.2
5 and above	138	31.4
Source of Income		
Business	71	16.1
Employed	13	3
Peasant Farmer	356	80.9

Utilization of Health Data for decision making

Utilization of health data for decision making was measured by establishing the participants' use of health

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XII Issue XV July 2025 | Special Issue on Public Health

services namely: HIV/AIDS prevention, Prevention of malaria, TB Prevention management, Child Immunizations, Hygiene and sanitation, Antenatal Clinic attendance and Deworming. The utilization of each category of health data for decision making was as follows: Prevention of malaria was at 187 (42.5%), TB prevention management was at 188 (42.7%), HIV/AIDS prevention was at 210 (47.8%), ANC was at 123 (28%), Deworming was at 146 (33.2%), immunization was at 156 (35.5%) and hygiene and sanitation was at 117 (26.6%).

One Key Informant at Nyando Sub- County hospital stated: *Communities will most of the times practice what they have information about. Therefore, in Nyando, the focus being mostly HIV/AIDS, the community members will also require information on the same* (KII$_4$). Another Key Informant observed that: "*utilization of health data for decision making is directly associated with the improved health seeking behaviour among the residents (*KII$_2$*).* The level of utilization of health data for decision making before the intervention is depicted in Table 2.

Table 2: Level of utilization of health data for decision before the intervention			
	Utilized (%)	Did Not utilize (%)	Total(%)
HIV/AIDS	210(47.8)	250(52.2)	440(100)
Prevention of malaria	187(42.5)	253(57.5)	440(100)
TB Prevention management	188(42.7)	252(57.3)	440(100)
Immunizations	156(35.5)	284(64.5)	440(100)
Hygiene and sanitation	117(26.6)	323(73.4)	440(100)
ANC	123(28)	317(72.0)	440(100)
Deworming	146(33.2)	294(66.8)	440(100)

Factors influencing utilization of health data for decision making

Utilization of health data for decision making was measured by establishing the participants' use of health services namely: HIV/AIDS prevention, Prevention of malaria, TB Prevention management, Child Immunizations, Hygiene and sanitation, Antenatal Clinic attendance and Deworming. The utilization of each category of health data for decision making was as follows: Prevention of malaria was at 187 (42.5%), TB prevention management was at 188 (42.7%), HIV/AIDS prevention was at 210 (47.8%), ANC was at 123 (28%), Deworming was at 146 (33.2%), immunization was at 156 (35.5%) and hygiene and sanitation was at 117 (26.6%).

One Key Informant at Nyando Sub- County hospital stated: *Communities will most of the times practice what they have information about. Therefore, in Nyando, the focus being mostly HIV/AIDS, the community members will also require information on the same* (KII$_4$). Another Key Informant observed that: "*utilization of health data for decision making is directly associated with the improved health seeking behaviour among the residents (*KII$_2$*).* The level of utilization of health data for decision making before the intervention is depicted in Table 3.

Table 3: Level of utilization of health data for decision before the intervention			
	Utilized (%)	Did Not utilize (%)	Total(%)
HIV/AIDS	210(47.8)	250(52.2)	440(100)
Prevention of malaria	187(42.5)	253(57.5)	440(100)
TB Prevention management	188(42.7)	252(57.3)	440(100)
Immunizations	156(35.5)	284(64.5)	440(100)
Hygiene and sanitation	117(26.6)	323(73.4)	440(100)

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XII Issue XV July 2025 | Special Issue on Public Health

ANC	123(28)	317(72.0)	440(100)
Deworming	146(33.2)	294(66.8)	440(100)

Factors influencing utilization of health data for decision making by communities

The study assessed the factors that influence the utilization of health data for decision making for improvement of the health seeking behaviour by community members. This was done by examining how the community members' socio-demographic characteristics and health service factors influenced the utilization of health data for making the decisions on prevention of malaria, TB prevention management, HIV/AIDS Management and Care, prevention and Immunizations of children, ANC, hygiene and sanitation, deworming. Several factors were examined including; The education level, religion, number of children per household, health facilities and services, gender and age.

Factors affecting utilization of HIV/AIDS data for decision making

On chi-square analysis to determine the association between independent variables and utilization of HIV/AIDS data for decision making, education level; religion; number of children in the household; and health facilities and services emerged to be the significant factors (P= 0.001, P=0.03, P=0.00, P=0.00 respectively). Chi-square analysis revealed that Gender (P=0.000), Environmental data (P=0.0023) and Religion (P=0.009) were the main factors affecting utilization of malaria prevention data by communities in Nyando sub-county. With regard to utilization of TB prevention data for decision making, the study established that Religion (P=0.000), Education level (P=0.001) and Age (P=0.024), were the strongest factors while Gender (P=0.177) and Health facilities (P=0.110) had no significant influence. On use of immunizations data, the study established that health facilities and services data (P=0.0004), gender (P=0.0344) and environmental data (P=0.0355) were the main factors. The findings are summarized in Table 4.

From logistic regression, participants who had secondary education levels were 2.5 times likely to use health data for decision making on HIV/AIDS prevention (Odd ratio=2.5, 95%Cl=1.62 3.89, p=0.00375) as compared to participants with primary level of education. Likewise, the odds of participants with secondary education levels were 2.3 times more likely to utilization of TB prevention data (Odd ratio=2.3, 95% Cl=1.51 3.54, P=0.00) compared to participants with primary level of education. Similarly, the odds of participants between age 18-30 years were 1.73 times in utilization of TB prevention data (Odd ratio=1.73, 95% Cl= 0.96 3.14, P=0.07) compared to age 51 years and above.

The odd of access to environmental health data was 2.81 times (Odd ratio=2.81, 95%Cl=1.12 7.47, P=0.001) with utilization of health data for decision making on malaria prevention compared to participants who were not able to access these environmental data while the odd of male participants was 0.26 times (Odd ratio=0.26, 95%Cl=0.14 0.44, P=0.00) compared to female participants in utilization of health data for decision making on malaria prevention. The odds of *access to health facilities and services data* for making decisions on immunization were 2.32 times (Odd ratio=2.32, 95%Cl=1.09 4.99, P=0.029) compared to participants who were not able to access the health facilities and services data. Details are presented in Table 5.

On corroboration of the above findings with views from key informants the study established that participants were in agreement with the factors described above. One Key Informant at Nyando Sub- County hospital stated: *Communities will most of the times practice what they have information about. Therefore, in Nyando, the focus being mostly HIV/AIDS, the community members will also require information on the same* (KII_4). Another Key Informant observed that: "*utilization of health data for decision making is directly associated with improved health seeking behaviour among the residents (*KII_2*).* Therefore, data should be disseminated to the communities in order for them to make informed choices pertaining to their health.

A female opinion leader who was a Key Informant had this to say: *there has been fatigue brewing in going for services such as ANC and child immunizations but now that we have had good conversations around the importance of using data, I will sensitize my neighbors and even share with them the resource materials available in order to move at the same pace.*

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XII Issue XV July 2025 | Special Issue on Public Health

Factors	Use of HIV/AIDS Data Yes n(%)	No n(%)	χ^2	P-Value	Use of Malaria Prevention Data Yes n(%)	No n(%)	χ^2	P-Value	Use of TB Prevention Data Yes n(%)	No n(%)	χ^2	P-Value	Use of Immunization Data Yes n(%)	No n(%)	χ^2	P-Value
Gender			0.9545	0.328			28.2964	0			1.817	0.1777			4.4751	0.034
Male	43 (45.3)	52 (54.7)			19 (20.0)	76 (80.0)			42 (44.2)	53 (55.8)			42 (44.2)	53 (55.8)		
Female	178 (51.6)	167 (48.4)			177 (51.3)	168 (48.7)			110 (31.9)	235 (68.1)			110 (31.9)	235 (68.1)		
Age Group			3.2677	0.234			12.4955	0.046			9.3748	0.0247			9.7487	0.02
18–30	48 (46.2)	56 (53.8)			45 (43.3)	59 (56.7)			31 (29.8)	73 (70.2)			31 (29.8)	73 (70.2)		
31–40	84 (53.8)	72 (46.2)			76 (48.7)	80 (51.3)			62 (39.7)	94 (60.3)			62 (39.7)	94 (60.3)		
41–50	37 (43.0)	49 (57.0)			42 (44.7)	52 (55.3)			20 (23.3)	66 (76.7)			20 (23.3)	66 (76.7)		
51+	52 (55.3)	42 (44.7)			–	–			39 (41.5)	55 (58.5)			39 (41.5)	55 (58.5)		
Education Level			13.0517	0.001			7.3582	0.025			13.0602	0.0015			2.3812	0.304
Primary	111 (43.0)	147 (57.0)			101 (39.1)	157 (60.9)			82 (31.8)	176 (68.2)			82 (31.8)	176 (68.2)		
Under Primary	12 (57.1)	9 (42.9)			11 (52.4)	10 (47.6)			7 (33.3)	14 (66.7)			7 (33.3)	14 (66.7)		
Secondary	63 (39.1)	98 (60.9)			84 (52.2)	77 (47.8)			63 (39.1)	98 (60.9)			–	–		
Religion			6.7576	0.034			9.291	0.009			14.3542	0.008			6.4141	0.04
Protestant	175 (50.7)	170 (49.3)			153 (44.3)	192 (55.7)			118 (34.2)	227 (65.8)			63 (39.1)	98 (60.9)		
Catholic	45 (52.9)	40 (47.1)			43 (50.6)	42 (49.4)			34 (40.0)	51 (60.0)			118 (34.2)	227 (65.8)		
Other	1 (10.0)	9 (90.0)			0 (0.0)	10 (100.0)			3 (30.0)	7 (70.0)			34 (40.0)	51 (60.0)		
No. of Children			10.79	0.004			6.8123	0.033			0.6053	0.7389			2.7488	0.253
4	106 (59.6)	72 (40.4)			92 (51.7)	86 (48.3)			66 (37.1)	112 (62.9)			66 (37.1)	112 (62.9)		
5	57 (46.0)	67 (54.0)			46 (37.1)	78 (62.9)			46 (37.1)	78 (62.9)			46 (37.1)	78 (62.9)		
5+	58 (42.0)	80 (58.0)			58 (42.0)	80 (58.0)			40 (29.0)	98 (71.0)			40 (29.0)	98 (71.0)		
Environmental Data			1.5835	0.208			9.2754	0.002			18.0604	0.034			4.4196	0.035

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XII Issue XV July 2025 | Special Issue on Public Health

Yes	20 (62.5)	12 (37.5)			23 (71.9)	9 (28.1)			17 (53.1)	15 (46.9)			17 (53.1)	15 (46.9)		
No	201 (49.3)	207 (50.7)			173 (42.4)	235 (57.6)			135 (33.1)	273 (66.9)			135 (33.1)	273 (66.9)		
Health Facilities			0.0072	–			0.8228	0.364			2.5469	0.1105			12.706	0
Yes	85 (39.5)	130 (60.5)			95 (42.2)	114 (53.0)			56 (26.0)	159 (74.0)			56 (26.0)	159 (74.0)		
No	136 (60.4)	89 (39.6)			19 (20.0)	130 (57.8)			128 (56.9)	97 (43.1)			96 (42.7)	129 (57.3)		

Factors	**Use of HIV/AIDS Data Yes n(%)**	**No n(%)**	**OR (95% CI)**	**P-Value**	**Use of Malaria Prevention Data Yes n(%)**	**No n(%)**	**OR (95% CI)**	**P-Value**	**Use of TB Prevention Data Yes n(%)**	**No n(%)**	**OR (95% CI)**	**P-Value**	**Use of Immunization Data Yes n(%)**	**No n(%)**	**OR (95% CI)**	**P-Value**
Gender																
Male	43 (45.3)	52 (54.7)	–	–	19 (20.0)	76 (80.0)	0.26 (0.14–0.44)	0	42 (44.2)	53 (55.8)	–	–	42 (44.2)	53 (55.8)	–	–
Female	178 (51.6)	167 (48.4)	–	–	177 (51.3)	168 (48.7)	Ref	–	110 (31.9)	235 (68.1)	–	–	110 (31.9)	235 (68.1)	–	–
Age Group																
18–30	48 (46.2)	56 (53.8)	–	–	45 (43.3)	59 (56.7)	2.05 (1.27–4.90)	0.027	31 (29.8)	73 (70.2)	1.73 (0.96–3.14)	0.07	31 (29.8)	73 (70.2)	–	–
31–40	84 (53.8)	72 (46.2)	–	–	76 (48.7)	80 (51.3)	2.14 (1.36–3.90)	0.032	62 (39.7)	94 (60.3)	1.20 (0.72–2.11)	0.45	62 (39.7)	94 (60.3)	–	–
41–50	37 (43.0)	49 (57.0)	–	–	42 (44.7)	52 (55.3)	–	–	20 (23.3)	66 (76.7)	–	–	20 (23.3)	66 (76.7)	–	–
51+	52 (55.3)	42 (44.7)	Ref	–	–	–	Ref	–	39 (41.5)	55 (58.5)	Ref	–	39 (41.5)	55 (58.5)	Ref	–
Education Level																
Primary	111 (43.0)	147 (57.0)	2.50 (1.60–3.89)	0.0038	101 (39.1)	157 (60.9)	1.71 (1.12–2.62)	0.013	82 (31.8)	176 (68.2)	2.30 (1.51–3.54)	0	82 (31.8)	176 (68.2)	–	–
Under Primary	12 (57.1)	9 (42.9)	–	–	11 (52.4)	10 (47.6)	–	–	7 (33.3)	14 (66.7)	–	–	7 (33.3)	14 (66.7)	–	–
Secondary	63 (39.1)	98 (60.9)	–	–	84 (52.2)	77 (47.8)	–	–	63 (39.1)	98 (60.9)	–	–	–	–	–	–
Religion																

INTERNATIONAL JOURNAL OF RESEARCH AND SCIENTIFIC INNOVATION (IJRSI)
ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XII Issue XV July 2025 | Special Issue on Public Health

Protestant	175 (50.7)	170 (49.3)	Ref	–	153 (44.3)	192 (55.7)	–	–	118 (34.2)	227 (65.8)	–	–	63 (39.1)	98 (60.9)	–	–
Catholic	45 (52.9)	40 (47.1)	0.14 (0.002–0.83)	0.049	43 (50.6)	42 (49.4)	–	–	34 (40.0)	51 (60.0)	–	–	118 (34.2)	227 (65.8)	–	–
Other	1 (10.0)	9 (90.0)	–	–	0 (0.0)	10 (100.0)	–	–	3 (30.0)	7 (70.0)	–	–	34 (40.0)	51 (60.0)	–	–
No. of Children																
4	106 (59.6)	72 (40.4)	2.13 (1.31–3.48)	0.002	92 (51.7)	86 (48.3)	–	–	66 (37.1)	112 (62.9)	–	–	66 (37.1)	112 (62.9)	–	–
5	57 (46.0)	67 (54.0)	–	–	46 (37.1)	78 (62.9)	–	–	46 (37.1)	78 (62.9)	–	–	46 (37.1)	78 (62.9)	–	–
5+	58 (42.0)	80 (58.0)	–	–	58 (42.0)	80 (58.0)	–	–	40 (29.0)	98 (71.0)	–	–	40 (29.0)	98 (71.0)	–	–
Environmental Data																
Yes	20 (62.5)	12 (37.5)	–	–	23 (71.9)	9 (28.1)	2.81 (1.12–7.47)	0.001	17 (53.1)	15 (46.9)	–	–	17 (53.1)	15 (46.9)	0.53 (0.35–0.81)	0.003
No	201 (49.3)	207 (50.7)	–	–	173 (42.4)	235 (57.6)	Ref	–	135 (33.1)	273 (66.9)	–	–	135 (33.1)	273 (66.9)	Ref	–
Health Facilities																
Yes	85 (39.5)	130 (60.5)	–	–	95 (42.2)	114 (53.0)	–	–	56 (26.0)	159 (74.0)	–	–	56 (26.0)	159 (74.0)	2.32 (1.09–4.99)	0.029
No	136 (60.4)	89 (39.6)	–	–	19 (20.0)	130 (57.8)	–	–	128 (56.9)	97 (43.1)	–	–	96 (42.7)	129 (57.3)	Ref	–

DISCUSSION

The study revealed low utilization of all health data constructs investigated with data on ANC (n=123 28%) and Hygiene and Sanitation (n=117, 26.6%) being the least utilized. This low utilization of health data to improve on health seeking behavior is also reflected in the respective disease indicators in the sub-county. The findings mirror a report by MOH (2018)[31] which revealed that Kenyans were sub optimally using health data for decision making despite efforts by the stakeholders to continuously collect data from the communities. This may suggest that the conventional methods of community sensitization and outreach programs that were being employed in the region had not yielded the desired outcomes across all the health indicators either.

The low utilization of health data may also may imply that there is limited interaction of community members with health personnel who are responsible for analyzing and sharing health data with communities. Additionally, it may also suggest that the conventional methods of conveying or disseminating data by health professionals are ineffective. This observation agrees with the findings of Gupta, et al, (2009)[32] in a study on utilization of health data among underserved communities in Nepal. The study revealed that underutilization of health data was mainly due to the less effective conventional health education strategies which often fell short in conveying messages that community members would understand and use to improve their health seeking behavior.

Similarly, the findings on low utilization of health data for decision making speak to the need for backflow of the health data to the community members who are the providers of the data. Studies by Walker & Jan, (2005)[33] emphasized the need to ensure that data flows back effectively to community members to ensure that it can relate to their local health needs so that decision making at the households presents a likelihood to increase behavior change based on the identified health needs.

The study presents several factors that determine health data use for decision making. Gender, Age, Religion, Education level, Environmental data and Health facilities and services data were significantly associated with utilization of health data for decision making by communities, Number of children per household was not significantly associated with health data use. These findings agree with a study by (Choy et al, 2014)[34] in China which revealed that higher educational level was an important factor that positively influenced the likelihood of household's participation and compliance with behavior change to improve health.

Similarly, the study findings align with the findings of a study done in Bangladesh by Hossain (2012) which showed that the factors that influenced utilization of hygiene and sanitation health data by rural women were education, profession, age, gender, region and socio-economic status. These findings also speak to an earlier study by Marlize, (2000)[16] which revealed that ethnicity, religion and religious beliefs, biological, psychological and personal history factors had strong influence on the people's decision to utilize health data. This finding was also affirmed in another study by Choy et al, (2014)[34] that gender, education and income were significantly associated with seeking for and utilizing health information. Hossain, (2012)[12] in a study in Ethiopia similarly reported that education, age, gender, region, socio-economic status, are key determinants health data needs.

On provision of feedback as a factor influencing utilization of health data, the findings were in line with Wanyoike (2012)[35] that provision of feedback was a motivation of those who collect it to use for their own benefit. The study however, from the qualitative findings, established that receiving feedback on health data provided increased odds of the community members using the to improve their health seeking behavior. The findings are consistent with those from a multicenter study conducted across 14 Asia-Pacific countries (Koo et al., 2012)[36], which revealed that Malaysia had the second lowest rate of health data utilization for decision making, standing at 38%. This reinforces the commonly held perception that the use of health data in decision making remains notably low in many low- and middle-income countries (LMICs).

CONCLUSION

The key factors found to influence utilization of health data included: Age, education level, religion and number of children per household.

Declarations

Funding: The research was funded by own sources of income.

Conflict of interest: The author is not conflicted in any way.

Ethical Approval: Ethical approval was obtained from Maseno University Ethics Review Committee and the National Commission for Science, Technology and Innovation.

REFERENCES

1. Tilahun, B., Teklu, A., Mancuso, A. et al. (2021). Using health data for decision-making at each level of the health system to achieve universal health coverage in Ethiopia: the case of an immunization programme in a low-resource setting. Health Res Policy Sys 19 (Suppl 2), 48. https://doi.org/10.1186/s12961-021-00694-1.
2. UNICEF (2024). UNICEF Digital Health and Information Systems 2024 Annual Report. United Nations Children Fund. Geneva.
3. Nutley, T., Gnassou, L., Traore, M., Bosso, A. E., & Mullen, S. (2019). Moving data off the shelf and into action: an intervention to improve data-informed decision making in Côte d'Ivoire. Global Health Action, 7, 10.3402/gha.v7.25035.
4. Thawer, S.G., Golumbeanu, M., Munisi, K. et al. (2022). The use of routine health facility data for micro-stratification of malaria risk in mainland Tanzania. Malar J 21, 345. https://doi.org/10.1186/s12936-022-04364-7.

5. Sally K., Julia, Walsh., Ndola, Prata., & Timothy, E., (2006). Information to Improve Decision Making for Health. Disease Control Priorities in Developing Countries. 2nd edition. The International Bank for Reconstruction and Development / The World Bank; New York: Oxford University Press.
6. Alyafei A, Easton-Carr R. (2024). The Health Belief Model of Behavior Change. May 19. In: StatPearls [Internet]. Treasure Island (FL): Stat Pearls Publishing; 2025 Jan–. PMID: 39163427.
7. Ritchie D, Van den Broucke S, Van Hal G. (2020). The health belief model and theory of planned behavior applied to mammography screening: A systematic review and meta-analysis. Public Health Nurs. 2021 May;38(3):482-492. doi: 10.1111/phn.12842. Epub Nov 30. PMID: 33258163.
8. Björkman, N., Martina, A., Jakob., S., David., Y. (2019). Reducing Child Mortality in the Last Mile: Experimental Evidence on Community Health Promoters in Uganda. American Economic Journal: Applied Economics 11 (3): 155–92.
9. Mboera, Leonard & Rumisha, Susan & Mbata, Doris & Mremi, Irene & Peter, Emanuel & Joachim, Catherine. (2021). Data utilisation and factors influencing the performance of the health management information system in Tanzania. BMC Health Services Research. 21. 498. 10.1186/s12913-021-06559-1.
10. Nutley, T., Gnassou, L., Traore, M., Bosso, A. E., & Mullen, S. (2014). Moving data off the shelf and into action: an intervention to improve data-informed decision making in Côte d'Ivoire. Global Health Action, 7, 10.3402/gha.v7.25035.
11. Rexhepi, Gadaf & Abazi, Hyrije & Rahdari, Amir & Angelova, Biljana. (2019). Open Innovation Models for Increased Innovation Activities and Enterprise Growth. 10.1007/978-3-030-16912-1_3.
12. Hossain S, Quaiyum MA, Zaman K, Banu S, Husain MA, Islam MA, et al. (2012) Socio Economic Position in TB Prevalence and Access to Services: Results from a Population Prevalence Survey and a Facility-Based Survey in Bangladesh. PLoS ONE 7(9): e44980. https://doi.org/10.1371/journal.pone.0044980.
13. Meghan Bruce Kumar, Regeru Njoroge Regeru, Kingsley Chikaphupha,, Lilian Otiso, Miriam Taegtmeyer, (2020). 'Do you trust those data?'—a mixed-methods study assessing the quality of data reported by community health workers in Kenya and Malawi, Health Policy and Planning, Volume 35, Issue 3, April, Pages 334–345, https://doi.org/10.1093/heapol/czz163.
14. Abias Asiimwe B., B. (2016). Determinants of Effective Utilization of Routine Health Information Within Private Health Facilities in Kampala-Uganda. Uganda Technology and Management University. Uganda.
15. MoH. (2020). The Kenya Community Health Strategy 2020-2025. Ministry of Health. Kenya.
16. Marlize Booman, Dave N. Durrheim, Kobus La Grange, Carrin Martin, Aaron M. Mabuza, Alpheus Zitha, Frans M. Mbokazi, Colleen Fraser, & Brian L. Sharp. Using a geographical information system to plan a Malaria control programme in South Africa. 2000.
17. Mukama, F., (2003). A Study of Health Information Systems at Local Levels in Tanzania and Mozambique: Improving the Use and Management of Information in Health Districts. [Online], Available: http://www.ub.uib.no/elpub/NORAD/2003/uio/thesis02.pdf [Downloaded: 24/11/2014 1:28 PM].
18. CHW Central (2025). Strengthening Community Level Support Health Chains. https://chwcentral.org/strengthening-community-level-health-supply-chains-in-kenya/
19. Rosenstock et al.1988 (1998). Social learning theory and the Health Belief Model. Health Educ Q. 1988 Summer;15(2):175-83. doi: 10.1177/109019818801500203. PMID: 3378902.
20. Yarinbab TE, Assefa MK. (2018). Utilization of HMIS data and its determinants at health facilities in east Wollega zone, Oromia regional state, Ethiopia: a health facility based cross-sectional study. Med Health Sci. 7(1).
21. McLeroy KR, Bibeau D, Steckler A, Glanz K. (1988). An ecological perspective on health promotion programs. Health Educ Q. Winter;15(4):351-77. doi: 10.1177/109019818801500401. PMID: 3068205.
22. Kenya National Bureau of Statistics. (2019). Statistical Abstracts. KNBS. Narobi. Kenya.
23. National Water and Storage Authority (2025). Flood Control. https://waterauthority.go.ke/nyando/
24. KNBS and ICF. (202)3. Kenya Demographic and Health Survey 2022. Key Indicators Report. Nairobi, Kenya, and Rockville, Maryland, USA: KNBS and ICF.
25. Labflow.(2025). Health Fcailities in Kisumu. https://labflow.org/health-facilities-in-kisumu-county/.
26. Mugenda, O.M. and Mugenda, A.G. (2003) Research Methods, Quantitative and Qualitative

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI | Volume XII Issue XV July 2025 | Special Issue on Public Health

Approaches. ACT, Nairobi.

27. KPHC. (2019). 2019 Kenya Population and Housing Census Reports. Vol III, 2019. Nairobi. Kenya.
28. Yamane, T. (1967) Statistics: An Introductory Analysis. 2nd Edition, Harper and Row, New York
29. Naing, et al. (2006). Practical Issues in Calculating the Sample Size for Prevalence Studies. Archives of Orofacial Sciences, 1, 9-14.
30. Nunnally, J. C. (1978). Psychometric theory. 2nd ed. New York: McGraw-Hill.
31. MoH. (2018). Health Information System Policy: Enhancing Health Information System for Evidence based Decision Making in the Health Sector. Ministry of Health. Kenya.
32. Shrestha S., Shrestha M., Wagle R.R., Gupta,B., (2020). Predictors of incompletion of immunization among children residing in the slums of Kathmandu valley, Nepal: A case-control study. BMC Public Health. 2020; 16:970. doi: 10.1186/s12889-016-3651-3.
33. Walker, Jan & Pan, Eric & Johnston, Douglas & Adler-Milstein, Julia & Bates, David & Middleton, Blackford. (2005). The Value of Health Care Information Exchange and Interoperability. Health affairs (Project Hope). Suppl Web Exclusives. W5-10. 10.1377/hlthaff.w5.10.
34. Choy, Lennon & Jing, Li. (2016). The role of higher education in China's inclusive urbanization. Cities. 60. 10.1016/j.cities.2016.04.008.
35. Wanyoike, J. (2012). Factors Influencing Use of Data for Decision Making in Community Health Prevention Programmes: A Case Study of APHIAplus, Nuru ya Bonde Nakuru County. Nairobi: University of Nairobi.
36. Koo, Jenn & Ching, Jessica & Yeoh, Khay-Guan & Wu, Deng-Chyang & Abdullah, Murdani & Cai, Quancai & Chiu, Han-Mo & Chong, Vui & Rerknimitr, Rungsun & Goh, Khean-Lee & Hilmi, Ida & Byeon, Jeong-Sik & Niaz, Khan & Siddique, Arif & Wu, Kai-Chun & Matsuda, Takahisa & Makharia, Govind & Sollano, Jose & Sung, Joseph. (2012). Knowledge of, attitudes toward, and barriers to participation of colorectal cancer screening tests in the Asia-Pacific region: A multicenter study. Gastrointestinal endoscopy. 76. 126-35. 10.1016/j.gie.2012.03.168.