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The Effectiveness of Using a Behavior Change Intervention to improve the Utilization of Health Data for Decision Making by the Communities of Nyando Sub-County, Kenya

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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 effectiveness of a Behavior Change Intervention on enhancing use of health data for decision making among community members in Nyando Sub- County, Kenya. 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, while qualitative data was analyzed using the NVivo application. McNemar's test confirm statistical significance of the differences in utilization of health data for decision making between the baseline and end-line. The results revealed statistical significance in the changes in utilization of health data recorded at the baseline and end-line phases of the study (P=0.019); hence concluding that the Behaviour Change Intervention was effective in enhancing utilization of health data for decision making by communities.*

Key Words: *Data, Health, Behaviour Change, Effectiveness, Utilization, Intervention, Communities*

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I. 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. 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. In Nyando Sub-County, there is still persistent poor health seeking behavior evidenced by poor health indicators. This calls for a paradigm shift in the way health data is communicated to communities. It is against the foregoing that this study tested the effectiveness of a Behavior Change Intervention in enhancing utilization of health data for decision making by the communities in Nyando Sub- County.

II. Literature Review

Science Direct (2025)[6] defines and effective intervention as the one where the change in one or more health outcomes is positive and statistically significantly different from baseline. According to Agyemang, S.& Wyss, K. .(2020)[7], the effectiveness of health programs throughout the world is dependent on the ability of

Program Managers and providers to identify health needs of the community members they serve; and to understand the extent to which their programmes address these needs.

Worth noting is the fact that the effectiveness of health data utilization for decision making in a community is directly linked to the performance of its communal governing systems (Asemahagn, 2017)[8]. A community is governed by rules, processes and systems which have the ability to support or hinder an individual's ability to use data in decision making (Ann, 2018)[9]. Enhancing community skills in health data use for decision making contributes to more advocacy for specific interventions for example in Water Sanitation and Hygiene (WASH), immunization for children drives (Shrestha et al, 2020)[10]. Studies also show that when community members use health information, they become confident, empowered and committed to participate in exploring solutions to their health challenges (MEASURE, 2016[11]; Haldane et al., 2023)[12].

A study in Rwanda (Niyigena, A., et al., 2022)[13] on the effectiveness on training of community members in data use established that community members advocated for better referral services that contributed to 20% increase in skilled attended deliveries by pregnant mothers (Shrestha et al, 2020)[10]. Another study in Zanzibar on data use for decision making, community data users confessed the importance of data in improving decision making: when the CHPs are well trained, they collect accurate data based on needs of the community; hence improvement in the community referral system at community level which should motivate them to have regular community dialogue as it creates the greatest CHPs (Campbell, C., et al. (2013)[14]. With data use, it can be easy to show the health status of a particular community; and community members can come together to agree on health priorities and key decisions made and followed up (Shrestha et al, 2020)[10]

Similarly, another study in Kenya by Mwangangi et, al., (2019)[15]established that community training on data use for decision making contributed to improved adherence to malaria preventive measures. Others studies in Kenya show significant improvement in data quality and reporting by community members. For example, in Kilifi, training of community health promoters and hence community members/households improved maternal health data completeness by 35%; while in Makueni, data sharing by community members during meetings increased HIV testing uptake by 40% (Braa et al, 2004[16]; Measure Evaluation, 2016[11]; Mohamed, A., 2021)[17]. Thus, training of community members is important in strengthening the overall health information system.

Behaviour Change Interventions (BCIs) are participatory, context-specific, and tailored to address behavioral drivers such as beliefs, social norms and habits while Conventional Health Education (CHE) is often passive, top-down, lecture-based, and focused on information dissemination with limited feedback loops (USAID SBCC Kit, 2021)[18]. BCIs empower households to interpret and act on personal health data hence shaping behavior, motivation and decision making while CHE tends to promote general health knowledge, not personal data use (USAID, 2021[18]; UNICEF, 2019)[19]. BCIs are tailored to local beliefs, practices, and contexts, therefore more relatable while CHE is often generic and less sensitive to cultural variations (Glanz et. al, 2022)[20]. BCIs include adaptive components and community-led tracking which CHE lacks (Figueroa et al., 2022)[21].

Behaviour Change Interventions (BCIs) offer several comparative advantages over Conventional Health Education (CHE) in improving households' utilization of health data for decision-making. While CHE traditionally focuses on disseminating information through lectures, posters, and printed materials, often using a one-way communication approach, BCIs focus on empowering households to become active participants in managing their health, building the motivation and confidence needed to translate data into action—rather than simply providing information with the expectation that change will follow automatically (Glanz et al., 201520[20]; Michie et al., 2011[22]; WHO, 2010)[23].

2.1 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.

2.1.1 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)[24]. 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.

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)[25].

2.1.2 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.

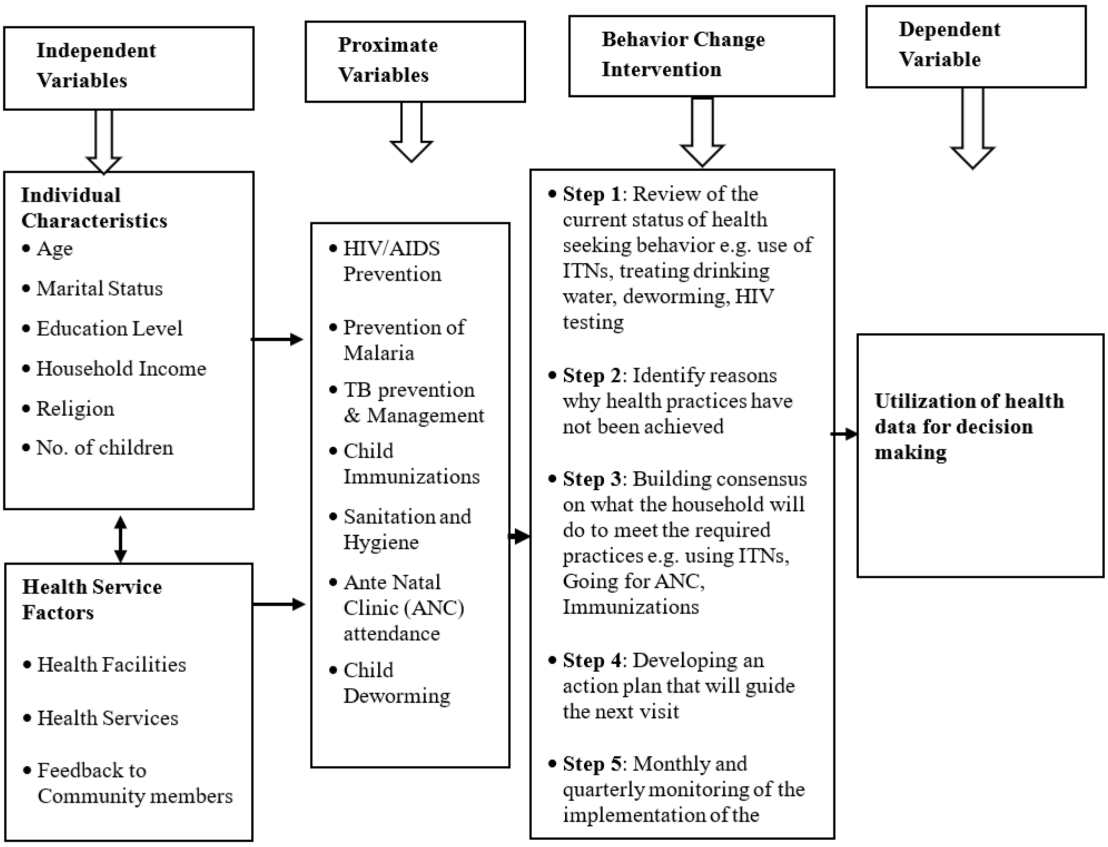

Figure 2.1: The Conceptual Framework (From reviewed Literature)

III. Methodology

3.1 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)[26]. The seasonal flooding contributes to WASH and also disease outbreak challenges (National Water and Storage Authority, 2025)[27]. 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)[28]. 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 (LabFlow, 2025)[29].

3.2 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)[30]. 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.

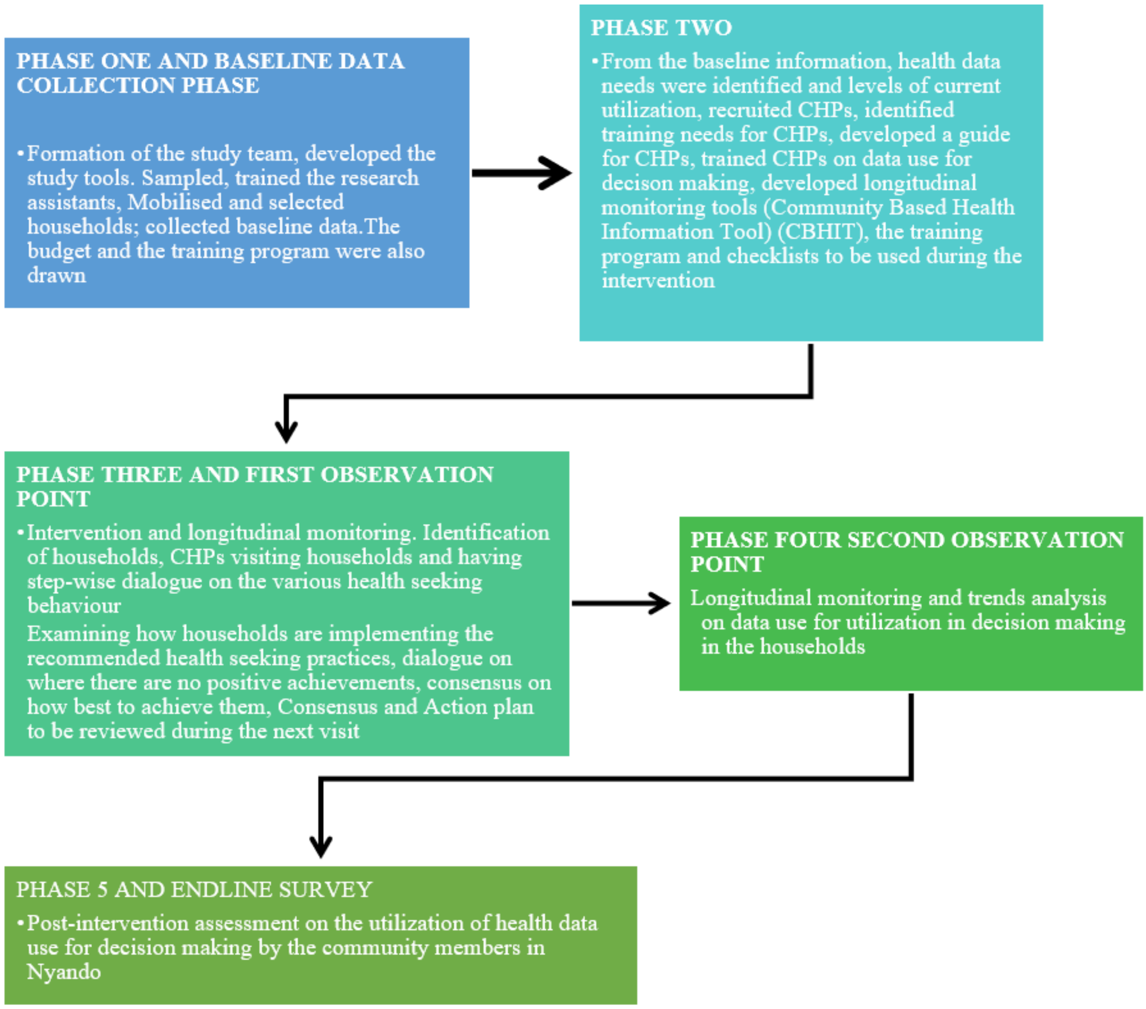

Figure 3.1: Flow chart of the Study Phases

3.3 Study Population

The target population: The target population comprised of the 77,121 heads households in Nyando Sub County (KPHC Vol III, 2019)[31] .

3.4 Inclusion Criteria

i) Nyando Sub County adults who were heads of households
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

3.5 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

3.6 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.

3.7 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)[30]. Taro Yamane (1967) [32] 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)[33]. 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.

3.8 Sampling Procedure

For Quantitative Data Multi-stage sampling and Probability Proportionate to Size (PPS) sampling were adopted (Mugenda and Mugenda, 2003)[29] 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.

3.9 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 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)[32].

3.10 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.

a. 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. Comparison of baseline and end line survey results for Health data use for decision making (Effectiveness) was carried out and McNemar test was used to establish the statistical significance of observed differences in utilization of health data use for decision making before and after intervention. The qualitative data was analyzed using NVIVO 14 application for thematic analysis.

b. 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.

IV.Results and Discussion

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 4.1.

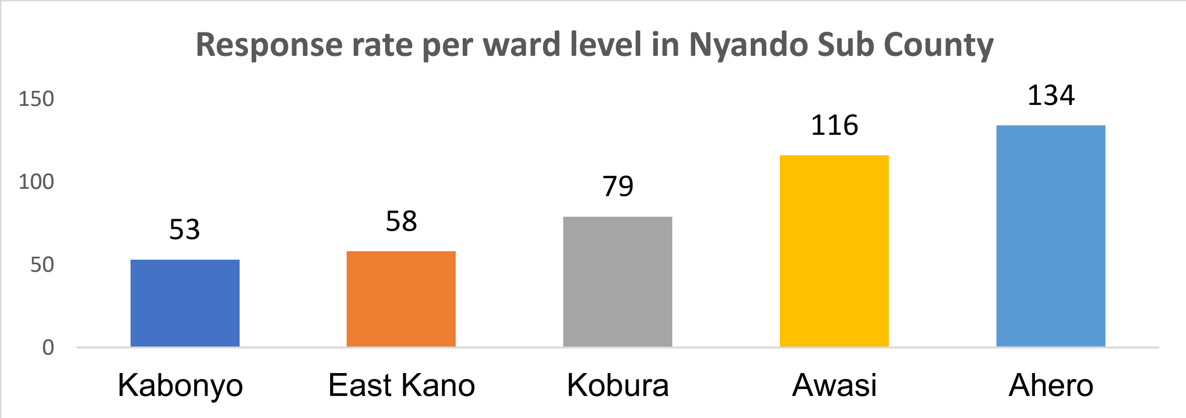

Figure 4.1 Response rate per ward level in Nyando Sub County

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 4.1.

Table 4.1 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

Effectiveness of the Behaviour Change Intervention in accelerating utilization of health data by communities
A comparison of the levels of utilization of health data for decision making **before** and at the end of the Behavior Change Intervention was used to establish the effectiveness of the intervention in achieving the desired results amongst the study participants. Effectiveness of the intervention was also assessed for each of the health data investigated.

Before the intervention, a total of 170(39.1%) respondents reported to be utilizing health data for decision making while 270(61.4%) reported not to have utilized any health data. After the 12months intervention, 378(85.9%) reported to be using health data for decision making giving an increase of 208(47.3%) as shown in **Figure 4.1**.

Using McNemer's test, the study established that the increase in proportion of those using health data for decision making after the intervention had strong statistical significance P=0.019 as demonstrated in **Table 4.2**.

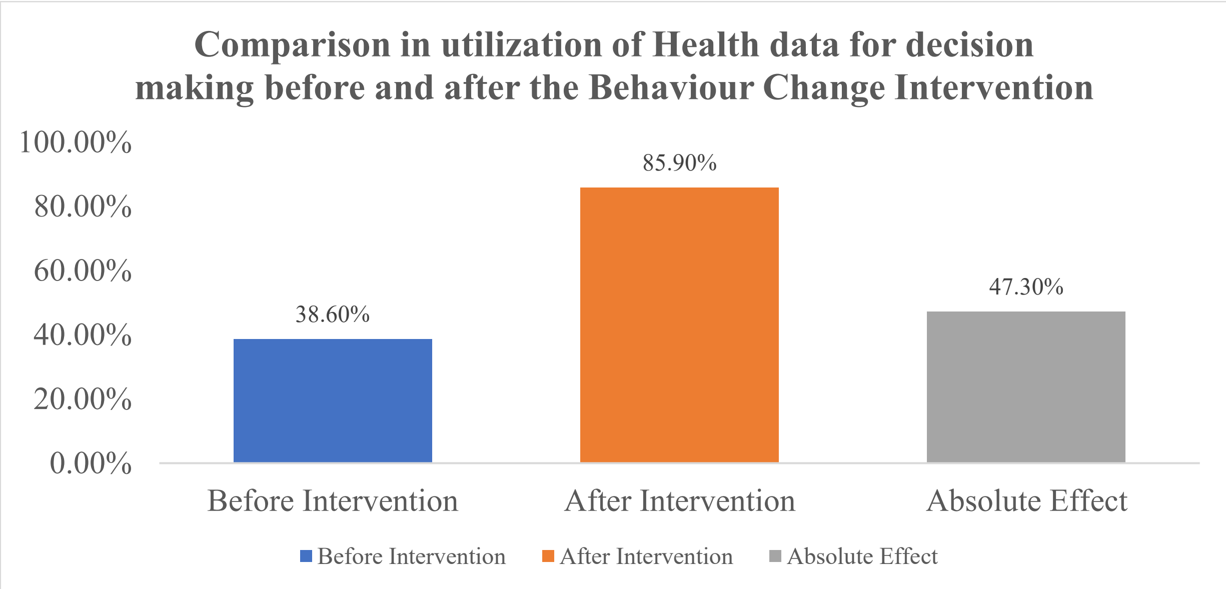

Figure 4.2: The Comparison between the utilization of health data needs for decision making

Likewise, significant statistical changes in the proportions using health data for decision making on individual health data before and after the intervention were also observed as illustrated in **Table 4.3** These findings therefore provided enough evidence to reject the Null Hypothesis that stated: "H_{01}: Behaviour Change Intervention is not effective for improving use of health data for decision making among communities in Nyando Sub County".

Table 4.2 Effectiveness of Health data utilization for decision making

Utilization of Health data	Utilization before Intervention	Utilization after Intervention	Effectiveness	McNemar Chi-square	P-Value
Yes	170(38.6%)	378(85.9%)	208(47.3%)	208	0.019
No	270(61.4%)	62(14.1%)			

Table 4.3 Effectiveness of the Behaviour Change Intervention in accelerating utilization of individual health data for decision making

Health Data	Utilization	Baseline n(%)	End line n (%)	Change n(%)	McNemar χ2	P-value
HIV/AIDS Prevention	Using	221(50.23)	401(91.14)	180(40.91)	170.53	0.000
	Not Using	219(49.77)	39(8.86)			
	Using	196(44.55)	396(90)	200(45.45)	200	0.000

Malaria prevention	Not Using	244(55.45)	44(10)			
TB Prevention	Using	233(52.95)	381(86.59)	148(33.64)	148	0.000
	Not Using	207(47.05)	59(13.41)			
Immunizations	Using	152(34.55)	308(70)	156(35.45)	156	0.000
	Not Using	288(65.45)	132(30)			
ANC	Using	159 (36.1%)	313 (71.1%)	154(35%)	106.83	0.000
	Not Using	281 (63.9%)	127 (28.9%)			
Hygiene and Sanitation	Using	239 (54.3%)	327 (74.3%)	88(20%)	34.883	0.003
	Not Using	201 (45.7%)	113 (25.7%)			
Deworming	Using	108 (24.5%)	236 (53.6%)	128(29.1%)	109.23	0.000
	Not Using	332 (75.5%)	204 (46.4%)			

Results from the qualitative survey confirmed the enhanced utilization of health data for decision making as stated by a client who visited a health facility for advice on healthy living with HIV. She stated: "*After listening to the Behaviour Change, I visited Nyando Sub County Hospital to enquire about HIV treatment services and I was appropriately advised*.". (Participant 2, FGD 1).

Another FGD discussant noted: *After the Behaviour Change dialogue on how to interpret and use health data for decision making, I have always taken my child to hospital for immunization without skipping any scheduled appointments* (Participant 2 FGD 3).

A Community Health Promoter (CHEP) who was one of the key informants said: *In our monthly review of the data on several indicators, we have noticed reduction in incidences of malaria, increase in mothers coming for ANC and also increase in number of children completing mandatory immunizations.*

V.Discussion

This study found a large increase of 45.4% in utilization of health data for decision making on Malaria Prevention, followed by 40.9 % for HIV prevention and Management, 35.4% for Immunization, 35.0% for ANC, 33.6% for TB ,29.1% on deworming and finally 20.0% in hygiene management. All these differences were confirmed as statistically significant by the McNemer test. This finding is in sync with those by a study done by Birhanu *et al.* (2012)33 in Ethiopia which posted similar correlation of utilization of data for decision making after a Behaviour Change intervention. However, the Ethiopian study recorded much higher levels in the increase in decision making using health data. These differences in the findings may be attributed to the levels of development in the health infrastructures and the health seeking behaviors in the two research areas. Whereas the Nyando Sub County communities have inadequately developed and understaffed health infrastructure, the Ethiopian population was endowed with better developed health infrastructure even at lower-level health facilities.

The findings of this study support AMREF (2013)[34] views that use of health data helps households in planning for healthcare, ensuring children are taken to hospital for immunizations until they complete all mandatory immunizations, women are able to go for ante natal clinics and deliver in health facilities; while other community members are able to go for HIV/AIDS treatment. With empowerment to make decisions, using the respondent's information which they provide, they are able to improve their children's feeding practices based on the trend of weight for age, strengthened through dialogue with the Community Health Promoters at household level (Jeremie, 2014)[35]. This study therefore affirms that Behavior Change has the effects of increasing utilization of health data for decision making. This was similar to another related research which reported that high rates of utilization of health data for decision making can be achieved by modifying the phases of the decisions process. Such modifications eventually lead to increased utilization of health data for decision making by reducing the barriers to decision making while amplifying their perceived benefits. The outcomes of such interventions increase possibilities of scheduling appointments for medical attention (Rodriguez MA, Bustamante AV, Ang A, *et al.* 2018)[36].

This study shows that the Behaviour Change Intervention presents a case of enablement for community members to use health data to improve their health and well-being; and be able to question the status quo as far as upward and downward accountabilities in community health systems is concerned. These findings resonate with those of Gharra et.al., (2022)[37], which reported that effectiveness of Behaviour Change Intervention was associated with increase in the uptake of Sexual Health services and led to its growing popularity as an effective tool for sustainable health behaviour change, an aspect that Studies by Gordon (2012)[38] agreed with confirming that health data was used to improve knowledge. The use of the knowledge gained enables decision making that may lead to quality health actions to improve overall individual and household health outcomes.

VI.Conclusion

McNemar's test confirmed that the increase in the proportion of those who were utilizing health data for decision making **before** and **after** the Behavior Change Intervention were statistically significant. Hence rejecting the Null Hypothesis that stated: "H_{01}: Behaviour Change Intervention is not effective for improving use of health data for decision making among communities in Nyando Sub County".

Our study has implications for the county government that given that the Behavior Change Intervention proved to be an effective model for enhancing utilization of health data for decision making by the communities, Nyando sub-county in particular and Kisumu County at large should consider mainstreaming Behavior Change Interventions in programs aimed at positively improving communities' health seeking behavior.

However, it is key to acknowledge the limitation of our study that this study focused on effectiveness of the Behaviour Change Intervention at the household level, there is need for a study of the entire health continuum from the household level, health facilities and the county health sector administration. Such a study will reveal whether utilization of health data at other levels of the health system continuum are effective in influencing overall behaviour change in utilizing heal data for decision making.

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