Use of Routine Health Data by County Health Management Teams in Kenya: Evidence from a Quasi-experimental Study

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ABSTRACT

Strengthening the use of routine health information is an essential element of effective health system governance in Kenya. Although the country has invested substantially in digital reporting platforms such as District Health Information System 2 (DHIS2), the integration of Routine Health Data into managerial planning and monitoring activities remains inconsistent across counties. County Health Management Teams (CHMTs) often meet reporting obligations but do not always translate the available information into evidence informed programme adjustments or performance review processes. This study examined the extent to which CHMTs use routine data in their decision making and assessed whether a structured capacity building programme could strengthen data use practices at the subnational level. A quasi-experimental approach supported by a Difference in Differences model was applied. Twelve counties were selected from the national regional economic blocs, with two chosen from each and allocated to either the intervention or control arm. Baseline data were collected from two hundred CHMT members in August 2024, followed by a nine-month intervention that involved targeted training sessions and continuous technical support. Endline data collection took place in April 2025. A key limitation of the study was the reliance on self-reported measures which may have been influenced by social desirability tendencies. The analysis produced a statistically significant treatment effect with a coefficient of 0.4593 and a p value of 0.0046. CHMTs in the intervention counties demonstrated notable improvements in incorporating routine data into programme monitoring policy development and adjustment of ongoing interventions. These shifts were not observed in the control counties. Further, subgroup analyses showed no statistically significant differences across gender, education level, age, or duration of CHMT membership. The findings indicate that structured capacity building initiatives can meaningfully strengthen routine data use among CHMTs. Sustaining these gains will require continued investment in analytical competencies and the institutionalization of routine evidence review processes within the devolved health sector.

Keywords: Routine health data; evidence-based decision-making; capacity-building; public health governance; Kenya; health information systems.

INTRODUCTION

A. Background to the Study

The use of routine health data for decision-making has become a cornerstone of health system strengthening globally. According to the World Health Organization's 2017 Framework and Standards for Country Health Information Systems, well-functioning health information systems are foundational to evidence informed planning, priority setting, and the systematic monitoring of health sector performance. Countries that effectively use routine data are better positioned to improve service delivery, allocate resources efficiently, and achieve universal health coverage targets.

Despite global acknowledgement of the value of routine health information, many health systems continue to struggle with transforming routinely collected data into meaningful inputs for management and planning. In several low- and middle-income settings, routine data systems generate substantial volumes of information, yet limited analytical capacity and weak data use cultures restrict their contribution to performance improvement

(Nutley and Reynolds, 2013; AbouZahr and Boerma, 2015). These constraints highlight the need to strengthen the institutional and technical conditions that enable routine data to inform health sector decisions.

Within sub-Saharan Africa, health information systems have expanded rapidly over the past two decades. Many countries have adopted digital reporting platforms such as the District Health Information Software 2 (DHIS2), improving the completeness and timeliness of health data reporting. Despite these advancements, evidence from across the region shows that health managers still underuse available data for operational and strategic decisions. Studies in Zambia, Tanzania, and Uganda have documented similar trends where data generated at facility and district levels are primarily used for reporting rather than for guiding planning, budgeting, or programme improvement (Mutale et al., 2013; Ndabarora et al., 2014). Barriers include inadequate data literacy, weak institutional support, limited human resource capacity, and a persistent culture of compliance reporting rather than analytical interpretation (Oware et al., 2025; Zeng et al., 2022). These challenges reveal that although data infrastructure has expanded, the behavioral and organizational conditions required to embed data use within core CHMT functions such as planning, priority setting, supervision, and performance review remain insufficiently developed.

The devolution of health services in 2013 fundamentally restructured Kenya's health governance arrangements by transferring considerable managerial authority to county governments (Ministry of Health, 2014). To support this shift, the Ministry of Health implemented the Kenya Health Information System, a DHIS2 based platform intended to standardize the collection, reporting, and analysis of routine health data nationwide (Ministry of Health, 2018). KHIS was designed to enhance evidence informed planning at both national and county levels, with County Health Management Teams expected to interpret and apply system generated data to guide resource allocation, human resource deployment, programme monitoring, and service delivery improvements (Oluoch et al., 2020).

Despite substantial gains in reporting completeness and digitalization through KHIS, persistent gaps remain in the actual use of routine data for managerial and policy decisions. National assessments have documented limited analytical capacity among county managers, weak feedback loops, and insufficient integration of data analysis within planning and budgeting processes (Ministry of Health, 2018). Empirical studies similarly note that many counties rely on informal practices and precedent rather than systematic review of routine health information when making operational decisions (Oluoch et al., 2020). These constraints have limited the ability of KHIS to function as an effective decision support tool, underscoring the continued need to strengthen data use culture within CHMTs to enhance efficiency, accountability, and overall health system performance.

B. Problem Statement

The ability of health systems to make timely, evidence-informed decisions depends on the effective generation, analysis, and utilization of routine health data. Despite global recognition of the importance of routine health information systems (RHIS) in improving health system performance, many developing countries continue to experience a persistent disconnect between data availability and its practical use in decision-making (Nutley & Reynolds, 2013; AbouZahr & Boerma, 2015). In sub-Saharan Africa, national investments in digital reporting platforms such as the District Health Information Software (DHIS2) have enhanced data reporting rates but have not translated into consistent evidence-based decision-making (Mutale et al., 2013; Ndabarora et al., 2014). Inadequate analytical capacity, poor data quality, and limited accountability mechanisms continue to undermine the transformation of data into actionable intelligence.

As a result, health managers frequently generate substantial volumes of routine data that remain underutilized, a pattern confirmed in recent Kenyan studies. Njuguna, Muiruri and Njoroge (2022) found that although public health facilities in Nairobi County routinely collected service data, limited analytical capacity and inconsistent participation in data review forums significantly constrained their use for planning and performance management. Likewise, Oware et al. (2025) reported that across fifteen counties, DHIS2 data were widely perceived as available but were often not applied in decision making due to inadequate analytic skills, low prioritization of data use, and reliance on a small group of technical officers rather than broader managerial engagement. These findings demonstrate that even where digital reporting systems are functional, routine data continue to have limited influence on resource allocation and programme adjustments within Kenya's health system. This underutilization represents a major bottleneck in the achievement of equitable, efficient, and accountable health systems.

Kenya mirrors this regional challenge despite significant progress in data collection and digitization through the District Health Information System 2 (DHIS2). The devolution of health services in 2013 transferred substantial decision-making authority to county governments, thereby heightening the need for strong data-use capacity among CHMTs. While reporting completeness within KHIS is relatively high in most counties, the system's data are still rarely used to guide operational or strategic decisions. Evidence from the Ministry of Health's National and County Health Budget Analysis FY 2018–2019 (Ministry of Health, 2019) and the Kenya Health Financing System Assessment (Dutta, Maina, Ginivan & Koseki, 2018) shows that many counties continue to base planning, budgeting, and staffing decisions on historical expenditure patterns, donor driven priorities, and political considerations rather than on systematic analysis of routine health data. This pattern is further reinforced by recent county level studies in Kitui and Marsabit, which found that managerial decisions were often influenced more by precedent and external pressures than by empirical evidence (Karijo, 2021; Aila, 2021).

Weak feedback systems limited analytical skills, and minimal institutional incentives for data use exacerbate this gap (Wako et al., 2018; O'Meara et al., 2022). This underuse of available data results in inefficient resource allocation, misaligned priorities, and reduced accountability within Kenya's devolved health system. Despite multiple policy frameworks advocating for evidence-based management, limited empirical research has systematically examined the types of decisions informed by routine health data at county level. This body of evidence highlights that existing literature, while documenting barriers and describing the limited application of RHD for planning and resource allocation (Masaviru, Namusonge, & Nambuswa, 2021; Muwonge et al., 2022), lacks causal evaluation of interventions designed to enhance the organizational and behavioural components of data use in devolved health systems (Wako et al., 2018; Nutley & Reynolds, 2013). This knowledge gap constrains efforts to strengthen evidence based public health management, underscoring the necessity of this study.

C. Objective of the Study

The overall objective of this study was to identify the most common public health decisions informed by routine health data at the county level in Kenya and to examine how capacity-building interventions influenced data-driven decision-making among CHMTs.

The study was guided by the following specific objectives:

1. To examine differences in the use of routine health data for public health decision-making between baseline and endline across intervention and control counties.
2. To assess variations in the use of routine health data for decision-making across selected demographic and institutional characteristics.
3. To evaluate the effect of a targeted capacity-building intervention on the integration of routine health data into county-level public health decision-making.

The study also sought to assess the following hypotheses:

1. **H_{01}:** There is no statistically significant difference in the use of routine health data for public health decision-making between intervention and control counties.

2. **H_{02}:** There are no statistically significant variations in the use of routine health data for decision-making across demographic and institutional characteristics.

3. **H_{03}:** The training intervention has no statistically significant effect on the integration of routine health data into public health decision-making among CHMTs.

D. Significance of the Study

This study holds important implications for policy and practice within Kenya's devolved health system. By identifying the specific public health decisions that draw most heavily on routine health data, it clarifies how evidence is actually applied within county governance structures. These insights help align future investments in health information systems with the decision areas of greatest managerial relevance. The study also contributes methodologically by demonstrating that structured capacity building can enhance the integration of routine data into decision making. This addresses a key gap in understanding how routine data are translated into actionable intelligence within everyday public health management. The findings are therefore valuable to policymakers, development partners, and county health managers seeking to institutionalize evidence informed governance and strengthen accountability in planning and resource allocation.

MATERIALS AND METHODS

A. Study Design and Setting

This study employed a quasi-experimental design with intervention and control groups. All forty seven counties in Kenya formed the initial sampling frame for the study. To ensure balanced representation of the country's major geographic and administrative contexts, the counties were first grouped into the six officially recognized regional economic blocs. From each bloc, two counties were randomly selected, resulting in a total of twelve counties. This approach provided a stratified structure to the sampling process, with stratification occurring at the bloc level and random selection occurring within each stratum. The final sample therefore reflected both geographic diversity and the organizational variation present across Kenya's devolved health system.

Six counties formed the intervention arm and received a structured capacity building programme grounded in a customized MEASURE Evaluation curriculum. The training was delivered over a nine-month period and comprised modular sessions on data quality assessment, indicator interpretation, basic statistical analysis, development of data review products, and application of routine data to planning and performance management. These modules were implemented through a blended approach that combined in person workshops, virtual coaching sessions, and on-site mentorship for CHMT members. The remaining six counties served as the control arm and did not receive any training during the study period. Baseline and endline data were collected from both groups to assess changes over time and to estimate the effect of the intervention on routine data use.

From the Lake Region Economic Bloc, Kisii served as the intervention county and Kisumu as the control. In the North Rift Economic Bloc, Uasin Gishu represented the intervention group and Turkana the control. Kiambu and Meru were drawn from the Mt. Kenya and Aberdare Bloc, Garissa and Marsabit from the Frontier Counties Development Council, Kilifi and Kwale from the JumuiyayaKaunti za Pwani, and Machakos and Makueni from the Southeastern Kenya Economic Bloc. This distribution provided a balanced cross-section of counties varying in resource capacity, infrastructure, and information system maturity.

The study was conducted within Kenya's devolved health system, where CHMTs are responsible for coordination, planning, and oversight of health service delivery (Government of Kenya, 2015; Muinga, Paton, & English, 2018). Each CHMT served as a unit of analysis since it functions as the central mechanism through which routine data are synthesized and translated into actionable decisions. Ethical approval was obtained from a recognized Institutional Review Board, and official authorization was granted by the Ministry of Health. All participants provided informed consent, and confidentiality was observed throughout the study.

B. Study Population and Sampling

The study targeted County Health Management Team members occupying administrative and technical positions responsible for health sector management in the selected counties. This multidisciplinary group comprised nurses, clinicians, health records officers, public health officers, and other senior administrators who collectively oversee planning, resource allocation, supervision, and monitoring of county health systems

(Government of Kenya, 2015; Muinga, Paton, & English, 2018). Sampling employed a combination of purposive and simple random techniques. The six regional economic blocs in Kenya were first purposively selected to ensure representation across diverse administrative and geographic contexts. Two counties were then randomly selected from each bloc, yielding twelve counties that were equally assigned to the intervention and control groups. All consenting CHMT members within the selected counties were enrolled in the study, generating a total sample of 200 participants. The same individuals were followed and surveyed at both baseline and endline, ensuring consistency in respondent identity and supporting the validity of the pre post and Difference in Differences analyses.

The sample size for this study was determined using Cochran's (1977) formula for proportions and incorporated explicit assumptions to ensure adequate statistical power. A standard normal value of $Z = 1.96$ was used to represent a 95 percent confidence level. Because the true proportion of CHMT members routinely using health data was unknown, an expected proportion of $p = 0.50$ was applied, which yields the maximum variance and therefore the largest possible sample size. The desired margin of error was set at 0.10, allowing the estimated proportion to vary within ten percentage points in either direction. Based on these assumptions, the minimum required sample size was calculated to be 192 CHMT members. To accommodate potential attrition, the target was increased to 200 participants, which constituted the final sample enrolled in the study.

C. Data Collection Procedures

Data were collected at two distinct time points, baseline and endline, to examine changes in the use of routine health data for decision-making among CHMTs. The baseline phase established the pre-intervention conditions for both the intervention and control counties, while the endline phase captured post-intervention outcomes following the implementation of the data-use capacity-building program. A structured selfadministered questionnaire was used as the main data collection instrument.

The data collection tool was developed in alignment with the study objectives and adapted from validated instruments commonly used in assessments of routine health information system performance. Core sections were drawn from the Performance of Routine Information System Management (PRISM) Diagnostic Tools developed by MEASURE Evaluation, which assess technical, organizational and behavioral determinants of routine data use. Additional items measuring decision making practices and data use frequency were also adapted.

Data collection was carried out by trained research assistants under the direct supervision of the principal investigator to maintain consistency and accuracy. Enumerators underwent comprehensive training on research ethics, confidentiality, and standardized administration of the questionnaire. Although the capacity building activities were delivered through scheduled training sessions, ongoing technical support, and structured learning materials over a nine-month, the use of self-reported data still presents the possibility of social desirability bias. Participants may have been inclined to portray their data use practices more favorably because they were aware of the intervention's objectives and had sustained exposure to training content.

D. Data Analysis Techniques

Data were analyzed using both descriptive and inferential statistical methods to address the study objectives. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were first computed to summarize respondent characteristics and provide an overview of baseline and endline patterns in the use of routine health data for decision-making. These descriptive analyses offered insights into how CHMTs applied data across key functional areas such as planning, budgeting, monitoring, and resource allocation.

Inferential analysis was performed to determine whether observed differences in data-use practices across groups and time periods were statistically significant. Chi square tests were used to examine differences in reliance on routine health data between baseline and endline across intervention and control counties, as well as across key demographic and institutional characteristics. Prior to analysis, the key assumptions for the chi square test were assessed. Specifically, all variables were categorical, observations were independent and

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expected cell counts were examined to ensure that no more than 20 percent of cells had expected frequencies below five and that no individual cell had an expected count of zero. These requirements were satisfied for all reported analyses, supporting the validity of the chi square results.

To strengthen causal inference, a Difference in Differences regression model was employed to compare changes in the outcome variable between intervention and control counties over time. The control group served as the counterfactual for estimating the net effect of the training. The validity of the DiD approach rests on the parallel trend's assumption, which was assessed prior to analysis. These checks showed no systematic differences in pre intervention slopes or levels between the two groups, providing reasonable support that the parallel trends assumption was met.

RESULTS

The results present quantitative evidence on how CHMTs apply routine health data within county health governance structures and how exposure to a structured capacity-building intervention shaped these practices. The analysis draws on baseline and endline data to provide a coherent account of patterns, variations, and measurable changes in data-informed decision-making across counties.

A. Socio-Demographic Characteristics of Respondents

Table 1 summarizes the key socio-demographic and professional characteristics of CHMTs members who participated in the study at baseline and endline across both intervention and control counties. The table highlights attributes such as gender, age, education level, and duration of CHMT membership, offering insight into the managerial diversity and institutional experience represented across counties.

Table 1: Socio-Demographic Characteristics of Respondents

Variable	Category	Baseline			Endline		
		Intervention	Control	Overall	Intervention	Control	Overall
Total Respondents		47.1% (90)	52.9% (101)	100.0% (191)	46.6% (89)	53.4% (102)	100.0% (191)
Age	20 - 29 Years	1.6% (3)	4.7% (9)	6.3% (12)	1.6% (3)	4.7% (9)	6.3% (12)
	30 - 39 Years	5.8% (11)	11% (21)	16.8% (32)	5.2% (10)	11% (21)	16.2% (31)
	40 - 49 Years	25.1% (48)	21.5% (41)	46.6% (89)	25.1% (48)	21.5% (41)	46.6% (89)
	50 Years and Above	14.7% (28)	15.7% (30)	30.4% (58)	14.7% (28)	16.2% (31)	30.9% (59)
Gender	Male	24.6% (47)	29.8% (57)	54.5% (104)	25.1% (48)	29.8% (57)	55% (105)
	Female	22.5% (43)	23% (44)	45.5% (87)	21.5% (41)	23.6% (45)	45% (86)
Education Level	Diploma Certificate	4.7% (9)	9.4% (18)	14.1% (27)	4.7% (9)	9.4% (18)	14.1% (27)

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	Master's Degree	13.6% (26)	15.2% (29)	28.8% (55)	13.6% (26)	15.2% (29)	28.8% (55)
	PhD	0.5% (1)	2.6% (5)	3.1% (6)	0.5% (1)	2.6% (5)	3.1% (6)
		28.3% (54)	25.7% (49)	53.9% (103)	27.7% (53)	26.2% (50)	53.9% (103)
CHMT Membership Duration	Less than 1 year	5.8% (11)	5.8% (11)	11.5% (22)	5.8% (11)	6.8% (13)	12.6% (24)
	2-5 years	26.7% (51)	24.1% (46)	50.8% (97)	25.7% (49)	26.2% (50)	51.8% (99)
	6-9 years	8.4% (16)	11% (21)	19.4% (37)	8.9% (17)	9.4% (18)	18.3% (35)
	10 years and above	6.3% (12)	12% (23)	18.3% (35)	6.3% (12)	11% (21)	17.3% (33)

Males accounted for 54.5% of respondents at baseline and 55% at endline, while females represented 45.5% and 45%, respectively. The dominant age group was 40–49 years, accounting for about 47% of respondents, followed by those aged 50 years and above, who comprised roughly 30%. Educational qualifications were generally high. More than half of all respondents held undergraduate degrees, and about onethird possessed master's-level qualifications, underscoring a technically competent and academically prepared workforce. Regarding tenure, approximately half of the respondents had served between two and five years on their CHMT, with another one-fifth having over a decade of experience.

B: Descriptive Statistics on Data Use for Common Public Health Decisions

The study also assessed the specific public health decision areas in which County Health Management Teams reported using routine health data. Table 2 presents the mean agreement scores for each decision domain at baseline and endline across intervention and control counties. The domains examined include planning and budgeting, advocacy and resource mobilization, programme monitoring and evaluation, intervention adjustment, policy and guideline development, and supply chain management.

Table 2: Distribution of Common Public Sector Health Decisions Informed by Routine Health Data

Variable	Baseline			Endline		
	Intervention	Control	Overall	Intervention	Control	Overall
I use routine health data to design plans, set priorities, allocate resources, and develop budgets.	3.72 (0.98)	3.78 (0.88)	3.75 (0.93)	4.11 (0.65)	3.59 (0.98)	3.83 (0.88)
I rely on routine health data for advocacy, resource mobilization, grant applications, and partnerships.	3.76 (0.84)	3.99 (0.77)	3.88 (0.81)	4.13 (0.74)	3.97 (0.72)	4.05 (0.73)
Routine health data guides my decisions on continuing, modifying, or ending interventions and addressing inequities.	3.84 (0.79)	4.05 (0.74)	3.95 (0.77)	4.27 (0.77)	4.01 (0.72)	4.13 (0.75)

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I use routine health data to monitor and evaluate programme performance, staff allocation, and training needs.	3.89 (0.89)	4.11 (0.77)	4.01 (0.84)	4.35 (0.71)	4.08 (0.79)	4.20 (0.76)
Routine health data informs my decisions on policies, guidelines, procurement, and distribution of essential supplies.	3.98 (0.79)	3.90 (0.88)	3.94 (0.84)	4.48 (0.61)	3.85 (0.85)	4.15 (0.81)
Common Decision Made Overall	3.86 (0.73)	3.99 (0.61)	3.93 (0.67)	4.27 (0.42)	3.91 (0.59)	4.08 (0.55)

The results show that routine health data were consistently used to support several core decisions making functions within county health management. Across both baseline and endline assessments, the most reported uses of data included planning and budgeting, programme monitoring and evaluation, intervention adjustment, advocacy and resource mobilization, policy and guideline development, and supply chain management. These domains recorded mean agreement scores close to or above four at endline in the intervention counties, indicating strong perceived reliance on data in these areas.

At baseline, overall mean agreement for common decision areas was moderately high in both groups, with intervention counties reporting 3.86 (SD = 0.73) and control counties 3.99 (SD = 0.61). The most frequently cited decisions involved planning functions and program monitoring, reflected in the relatively higher baseline means in these categories. By endline, notable increases were observed across all decision domains in the intervention counties, where the overall mean rose to 4.27 (SD = 0.42). This was particularly evident in decisions related to policy development and monitoring and evaluation, which showed the largest gains. In contrast, the control counties showed minimal change over time, with an endline mean of 3.91 (SD = 0.59).

These patterns suggest that routine data most informed day to day governance tasks such as priority setting, resource allocation, tracking program performance, adjusting interventions, guiding procurement and distribution of supplies, and supporting advocacy efforts. The marked improvements in the intervention arm indicate that capacity strengthening contributed to more systematic and deliberate use of routine data across these decision domains, while the relative stability in the control arm highlights the absence of comparable change without structured support.

To complement the quantitative comparisons presented in Table 2, Figures 1 and 2 visualize how reliance on routine health data shifted over the study period in both intervention and control counties. Figure 1 summarizes the distribution of CHMT members reporting strong, partial, or limited reliance on routine data for their core decision making functions, providing a snapshot of how patterns of data use differed between groups at baseline and endline. Figure 2 presents the corresponding change in mean reliance scores, highlighting overall shifts in data use intensity across the two study arms. Taken together, the figures illustrate the extent to which routine data became more consistently integrated into managerial practice following the capacity strengthening intervention.

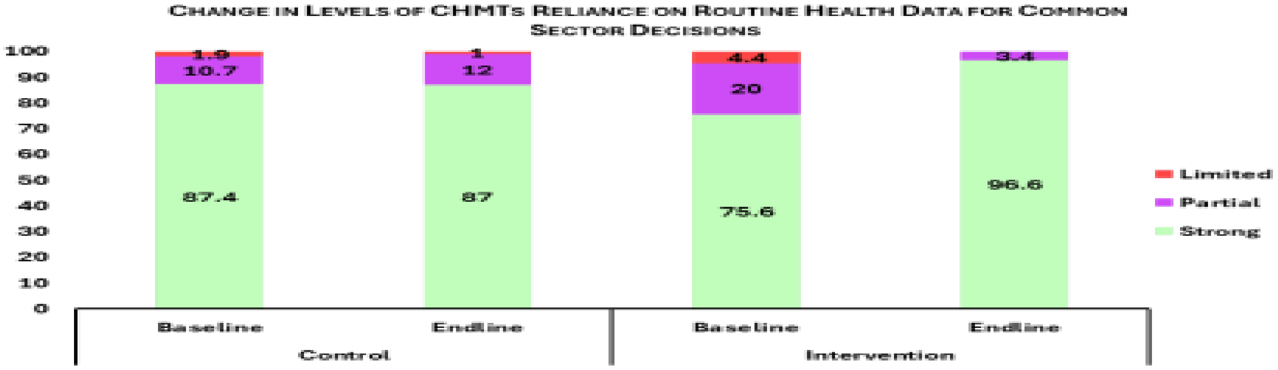

Figure 1: Change in Levels of CHMTs Reliance on Routine Health Data for Common Public Sector Health Decisions

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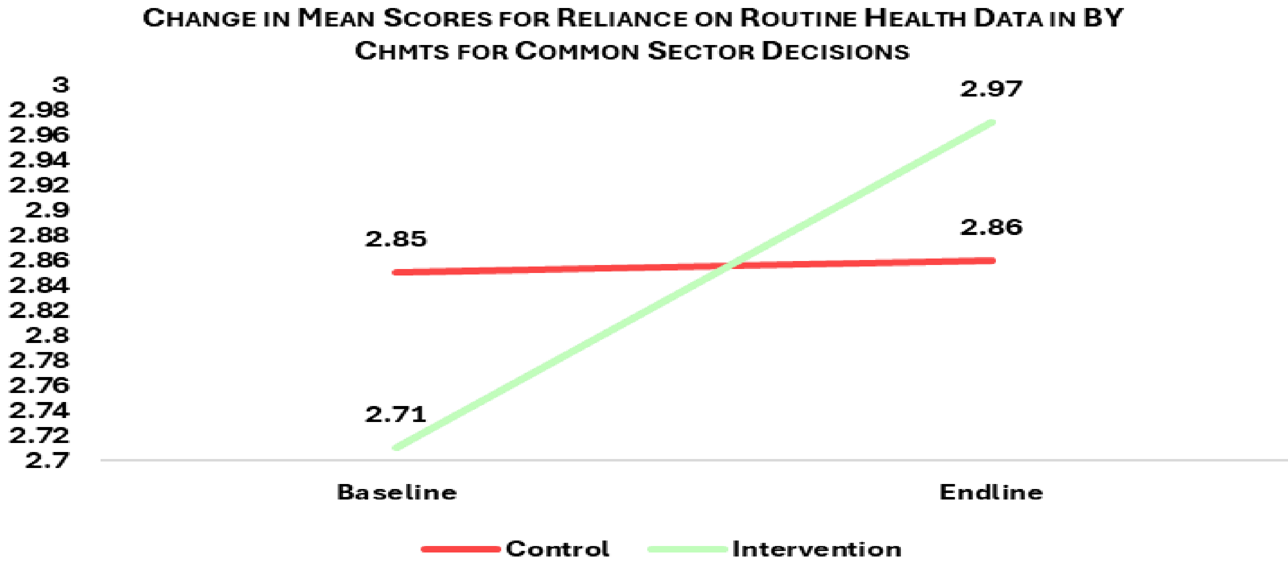

Figure 2: Change in Mean Scores for Reliance on Routine Health Data in By CHMTs for Common Public Sector Health Decisions

As illustrated in Figures 1 and 2, reliance on routine health data for key public health decisions increased substantially in the intervention counties while remaining largely unchanged in the control group. At baseline, 75.6 percent of CHMT members in the intervention counties reported strong reliance on routine data compared to 87.4 percent in the control counties. By endline, this proportion rose to 96.6 percent among the intervention group, and the limited reliance category was no longer observed. The control counties showed minimal variation in these categories over the same period.

The pattern is further reflected in the mean reliance scores. In the intervention counties, the mean score increased from 2.71 at baseline to 2.97 at endline, indicating a measurable strengthening in the consistency with which routine data were applied to managerial decisions. By contrast, the control counties exhibited virtually no change, with mean scores shifting only slightly from 2.85 to 2.86. These results highlight a clear divergence between the two study arms, with intervention counties demonstrating progressively stronger integration of routine data into decision making processes following the capacity strengthening activities.

C. Inferential Statistics

Inferential analysis using chi-square tests was conducted to determine whether the use of routine health data for public health decision-making differed significantly across time and between the intervention and control counties, and whether variations existed across demographic and institutional characteristics. The analysis addressed the first two study objectives by assessing temporal and cross-sectional differences in data use patterns and exploring how demographic factors such as gender, education level, tenure, and age intersected with institutional adoption of evidence-based practices.

Table 3: Chi-square Test for Common Health Sector Decisions Informed by Routine Health Data

Comparison	N	$\chi2$	df	p-value
Control: Baseline vs Endline	203	0.53	2	0.768
Intervention: Baseline vs Endline	179	13.23	2	0.001
Baseline: Control vs Intervention	193	7.85	2	0.02
Endline: Control vs Intervention	189	2.12	2	0.347

Control vs Intervention by gender	382	7.4	4	0.116
Control vs Intervention by Education Level	381	9.62	8	0.292
Control vs Intervention by Duration CHMT Membership	382	7.2	8	0.515
Control vs Intervention by Age	382	9.13	8	0.331

Results indicated variation in temporal change between the study arms. In the control counties, no statistically significant difference was observed between baseline and endline, χ^2 (2, N = 203) = 0.53, p = 0.768, suggesting that reliance on routine health data remained stable over time in the absence of targeted intervention. In contrast, the intervention counties recorded a significant shift, χ^2 (2, N = 179) = 13.23, p = 0.001, reflecting strengthened integration of data into decision-making processes following capacity-building efforts. Baseline comparisons showed significant differences between the intervention and control counties, χ^2 (2, N = 193) = 7.85, p = 0.020, indicating that the two groups did not begin at identical levels of routine data use. This difference does not in itself threaten internal validity because the Difference in Differences approach explicitly adjusts for any fixed pre intervention differences between groups. By estimating change over time rather than relying on baseline levels, the DiD model accounts for uneven starting conditions and isolates the net effect of the intervention. However, by endline, this variation had dissipated, χ^2 (2, N = 189) = 2.12, p = 0.347, indicating that structured training not only enhanced reliance on routine data but also harmonized datause practices across counties.

Further, the analysis revealed that gender, education, CHMT tenure, and age did not significantly influence reliance on routine health data, with all p-values exceeding the conventional 0.05 threshold. This pattern underscores that improvements in the intervention counties were uniformly distributed across demographic and professional categories rather than confined to specific groups. These findings suggest that structured interventions can foster a shared professional culture of data-informed governance, where the use of routine health information becomes an institutional rather than individual attribute.

To strengthen inference, the study also sought to assess the causal effect of the training intervention on the integration of routine health data into county-level decision-making. A Difference-in-Differences (DiD) framework was therefore applied, using control counties as the counterfactual to estimate how reliance on data would have evolved in the absence of the intervention. The DiD model provided a more rigorous estimation of the intervention's contribution to institutionalizing data use within health sector governance.

Table 4: DiD Regression Results for Common Health Sector Decisions

Term	**Estimate**	**Std. Error**	**t-value**	**p-value**	**95% CI (Lower, Upper)**
Intercept (Control Baseline)	3.9821	0.0785	50.70	<0.001	[3.8272, 4.1370]
Intervention (Baseline Difference)	-0.0712	0.1148	-0.62	0.5360	[-0.2975, 0.1551]
Post (Time Effect in Control)	-0.0225	0.1110	-0.20	0.8391	[-0.2401, 0.1951]
Intervention × Post (Treatment Effect)	0.4593	0.1605	2.86	0.0046	[0.1449, 0.7737]

The DiD regression yielded a statistically significant treatment effect of $\beta = 0.4593$ (SE = 0.1605, t = 2.86, p = 0.0046, 95% CI [0.1449, 0.7737]). This implies that, on average, exposure to the training intervention

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increased the mean reliance score on routine health data by approximately 0.46 units relative to the control group, after adjusting for time and baseline differences. The intercept ($\beta = 3.9821$, $p < 0.001$) reflected already strong baseline reliance on data among CHMT members, while the non-significant baseline difference ($p = 0.536$) confirmed comparability between intervention and control counties prior to the training. The non-significant time effect in the control group ($p = 0.839$) indicated that reliance levels remained stable over time in the absence of structured capacity-building, reinforcing that the observed change was attributable to the intervention itself.

The findings of the study underscore the transformative role of structured capacity-building in strengthening the use of routine health data within county-level public health decision-making. Descriptive results demonstrated clear improvements in data utilization across strategic areas signalling a culture of evidence-informed management. Inferential analysis further supported this trend, showing that counties exposed to the intervention demonstrated stronger and more consistent integration of data into managerial processes compared to those without targeted support. Accordingly, the findings illustrate how deliberate investments in managerial competencies can elevate data use from an administrative exercise to an institutionalized governance practice, embedding evidence at the centre of decision-making and fostering greater accountability and performance within Kenya's devolved health system.

DISCUSSION

A. Interpretation of Findings

The study demonstrated that structured capacity-building interventions significantly enhanced the integration of routine health data into public health decision-making at the county level. CHMTs in intervention settings exhibited a clear shift toward systematic and consistent data use in planning, budgeting, monitoring, and policy formulation. This pattern signaled a shift away from reporting carried out primarily for compliance purposes toward a more intentional use of routine data to guide planning, resource allocation, and performance management. The findings further showed that improvements were broadly distributed across demographic and institutional characteristics, suggesting that the intervention effectively cultivated a shared culture of data-driven decision-making. The observed strengthening of data reliance points to the growing recognition of routine health information not merely as a reporting requirement but as a managerial resource critical to performance optimization, resource accountability, and adaptive planning within Kenya's devolved health framework.

B. Comparison with Existing Literature

These findings align with broader evidence from low- and middle-income countries that emphasize the role of institutional capacity-building in bridging the gap between data production and use. Studies by Nutley and Reynolds (2013) and Aqil et al. (2014) similarly highlight that health information systems achieve impact only when data users are empowered with both technical skills and organizational support. The enhanced data utilization among CHMTs mirrors outcomes reported in Uganda and Tanzania, where targeted mentorship and decision-support training substantially improved data-driven planning and supervision (Nsubuga et al., 2018; Mboera et al., 2020). Moreover, the absence of demographic disparities in data-use practices resonates with findings by Hotchkiss et al. (2012), who argue that institutional reforms, rather than individual attributes, are the key determinants of sustained information use.

C. Implications for County Health Governance

The findings have several implications for strengthening Kenya's devolved health governance, particularly in promoting systematic and transparent use of routine health data at county level. By showing that structured capacity building can enhance data use among CHMTs, the study highlights the importance of sustained investment in health information governance. Counties could reinforce these gains by integrating data use modules into induction and leadership development programs for senior health managers, ensuring continuity even during administrative transitions. Moreover, institutionalizing regular data review forums would help embed evidence informed decision making into routine management processes. For example, counties could establish monthly CHMT performance review meetings anchored on KHIS dashboards, quarterly interdepartmental data review sessions focused on priority programs such as RMNCAH or HIV, and annual county health sector performance dialogues where data guide planning and budgeting decisions. Creating standardized agendas, templates, and reporting cycles for these forums would further promote consistency and accountability. The findings suggest that embedding routine data appraisal within existing managerial structures provides a practical pathway for counties to strengthen collective learning and improve alignment between evidence and resource allocation.

CONCLUSION AND RECOMMENDATIONS

A. Summary of Conclusions

The study established that structured capacity-building interventions significantly strengthened the integration of routine health data into county-level decision-making processes in Kenya. CHMTs exposed to targeted training demonstrated marked improvements in their ability to use data for planning, resource allocation, programme monitoring, and policy formulation. These findings suggest that strengthening analytical competencies and providing structured managerial support are associated with increased use of routine data for planning and performance review, reflecting a shift toward more evidence informed decision making among CHMTs. Moreover, the uniformity of improvements across gender, educational, and tenure categories highlights that the intervention's impact was both inclusive and sustainable. The study concludes that institutionalizing evidence-based practices through continuous professional development and supportive governance structures is essential for achieving effective, transparent, and adaptive health system management within Kenya's devolved framework.

B. Policy and Practice Recommendations

The findings underscore the need for a national framework to institutionalize the use of routine health data as a mandatory component of decision-making across all county health departments. The Ministry of Health, in collaboration with county governments, should embed data-use capacity-building within the continuous professional development programs for health managers. Counties should also establish regular data review forums where CHMTs jointly analyse, interpret, and apply evidence to guide planning and budgeting cycles. Integrating data analytics competencies into leadership training curricula will further ensure that decision-makers not only access data but can interpret and act on it effectively. Additionally, investment in digital infrastructure and interoperability between health information systems will enhance the accessibility, timeliness, and reliability of data required for managerial decision-making. Strengthening accountability mechanismscan help entrench data use as a governance norm across all administrative tiers.

C. Suggestions for Further Research

Future studies should extend this work by exploring the long-term sustainability of data use practices beyond the immediate post intervention period. Longitudinal studies could assess whether improvements in data driven decision making translate into measurable gains in health outcomes, resource efficiency, and service delivery equity. Further qualitative research is also recommended to examine how organizational culture, leadership dynamics, and political contexts shape the uptake of data for decision making within devolved systems. Comparative analyses across sectors such as education, agriculture, or social protection could provide broader insights into how data use interventions can be scaled and adapted to other governance domains. Equally important can be sustained research on data use ecosystems will be vital to informing policies that institutionalize evidence as the foundation for responsive, transparent, and accountable governance across Kenya's public service.

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