

# Impact of Community Health Promoters on Kenya's Devolved Healthcare: Mixed-Methods Analysis of 47 Counties

John Kanyaru

[jmkanyaru@gmail.com](mailto:jmkanyaru@gmail.com)

University of Hertfordshire

Mercy Njeru

Agripsych Beam Ltd

Bonface Muli

Matakiri Tumaini Centre

Rose Micheni

Tharaka-Nithi County Government

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## Research Article

**Keywords:** Community Health Promoters, devolved healthcare, Kenya, digital health, disease surveillance, capacity building, health information systems, mixed methods, qualitative research

**Posted Date:** February 27th, 2026

**DOI:** <https://doi.org/10.21203/rs.3.rs-8732386/v1>

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**Additional Declarations:** No competing interests reported.

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# Abstract

This mixed-methods study assessed Community Health Promoters' (CHPs) impact on healthcare delivery across Kenya's 47 counties. Data from 3,158 stakeholders including County Health Directors, CHPs, and community residents revealed significant improvements in disease detection: malaria reduction (34%,  $p < 0.001$ ), tuberculosis case finding (+ 42%,  $p < 0.001$ ), hypertension screening coverage (+ 56%,  $p < 0.001$ ), and diabetes referrals (+ 38%,  $p < 0.01$ ). Critical infrastructure gaps emerged, with only 23% of CHPs having consistent digital connectivity and 67% reporting real-time data transmission challenges. County variation was significant ( $F = 12.43$ ,  $p < 0.001$ ), with technology access explaining 47% of effectiveness variance ( $R^2=0.47$ ,  $p < 0.001$ ). Training needs include digital literacy (89%), non-communicable disease management (76%), and mental health first aid (82%). Qualitative findings from 235 transcripts identified four overarching themes: technology as transformative but inequitably distributed; supervision as variable and under-resourced; NCD management as an emerging but unmet mandate; and data sharing failures as system governance failures. Triangulation of quantitative and qualitative findings confirmed convergence across major themes while revealing important discordances around supervision quality metrics. Recommendations include systematic digitalisation of CHP workflows, standardised capacity building, and integration into county health information systems to advance Universal Health Coverage.

## 1. Introduction

Kenya's 2010 Constitution devolved healthcare services to 47 county governments, fundamentally transforming health service delivery and creating new opportunities for community-based health interventions (Ministry of Health, 2014). Within this devolved structure, Community Health Promoters (CHPs) have emerged as essential frontline health workers, bridging the gap between formal health facilities and communities, particularly in rural and underserved areas where healthcare access remains limited (Olang'o et al., 2020).

The Community Health Strategy, initially launched in 2006 and revised in 2014 and 2020, envisions a network of over 200,000 CHPs across Kenya providing health promotion, disease prevention, and basic curative services at household and community levels (Ministry of Health, 2020). Each CHP serves approximately 20–50 households within a defined Community Health Unit (CHU), working under the supervision of Community Health Assistants (CHAs) and reporting to facility-based health workers. This model aligns with global evidence supporting community health workers as cost-effective interventions for improving health outcomes, particularly for maternal and child health, infectious diseases, and increasingly for non-communicable diseases (Bhutta et al., 2010; Nkonki, L, Tugendhaft, A & Hofman, K, 2017; Jaskiewicz & Tulenko, 2012), and contributes to the broader vision of scaling community health worker programs across sub-Saharan Africa (Singh & Sachs, 2013).

However, the effectiveness of CHPs within Kenya's devolved system faces multiple challenges. Data sharing mechanisms among CHPs and with higher health system cadres remain inadequate, with most

CHPs relying on paper-based reporting that creates delays in disease surveillance and response (Njuguna et al., 2018). Training and capacity building vary significantly across counties due to resource disparities and lack of standardised approaches (Musoke et al., 2019). Furthermore, integration of digital health technologies to support CHP workflows has been inconsistent, despite evidence of their potential to improve data quality, supervision, and decision support (Agarwal et al., 2015).

This study addresses these knowledge gaps through comprehensive assessment of CHP impact across all 47 Kenyan counties, examining: (1) health outcomes for communicable and non-communicable diseases; (2) data sharing mechanisms and challenges; (3) capacity building and training needs; and (4) the role of digital health technologies in enhancing CHP effectiveness. Understanding these dynamics is critical as Kenya pursues Universal Health Coverage, where CHPs are positioned as key contributors to achieving equitable access to quality healthcare services.

## **2. Research Methodology**

### **2.1 Study Design and Rationale for Mixed Methods Design**

This study employed a convergent parallel mixed-methods design, simultaneously collecting and analysing quantitative and qualitative data across all 47 Kenyan counties between January 2023 and December 2024. The design enabled triangulation of findings from multiple data sources and stakeholder perspectives to provide a comprehensive assessment of CHP impact within Kenya's devolved healthcare system.

A convergent parallel mixed methods design was selected because neither quantitative nor qualitative methods alone could adequately address the multi-dimensional research questions. Quantitative methods are essential for measuring the magnitude of health outcome changes at national scale, establishing statistical relationships between technology access and CHP effectiveness, and generating findings generalisable across all county categories. However, quantitative data alone cannot explain the contextual mechanisms, lived experiences, and systemic barriers that account for substantial inter-county performance variation ( $F=12.43$ ,  $p<0.001$ ), nor can they capture the nuanced challenges that CHPs, health managers, and communities attribute to data sharing failures and training gaps.

Qualitative methods are required to generate the explanatory depth that gives meaning to quantitative patterns: understanding why counties with similar resource endowments achieve divergent outcomes, how CHPs experience and navigate digital health technology constraints, and what systemic governance factors enable or undermine program effectiveness. Qualitative data from key informant interviews and focus group discussions provide contextual validity and practitioner-generated insights that strengthen the policy relevance of findings (Creswell & Plano Clark, 2018). The convergent parallel design in which quantitative and qualitative data are collected simultaneously, analysed independently, and merged at the interpretation stage was preferred over sequential designs because it permits triangulation of findings from complementary sources without privileging either tradition (Creswell & Plano Clark, 2018).

This design is particularly appropriate for national-scale health program evaluations where both accountability evidence and contextual understanding are essential prerequisites for actionable policy recommendations (Palinkas et al., 2011).

**Mixed Methods Appraisal Tool (MMAT, 2018) Assessment.** The study design was appraised using the MMAT Version 2018 (Hong et al., 2018), which evaluates convergent mixed methods studies against five criteria: (1) Research questions addressed by both quantitative and qualitative components – MET: four research questions were specified and both methods components address each question complementarily. (2) Qualitative and quantitative data collected concurrently and consistently – MET: all data were collected between January 2023 and December 2024 using standardised instruments across all 47 counties. (3) Qualitative components meet quality criteria – MET: purposive sampling, verbatim transcription, dual independent coding with inter-coder reliability of 0.87, and data saturation monitoring were employed (see Sections 2.3 and 2.4). (4) Quantitative components meet quality criteria - MET: stratified random sampling, validated survey instruments, DHIS2 administrative data, and appropriate statistical methods were employed (see Sections 2.2 and 2.4). (5) Qualitative and quantitative data are integrated and findings adequately interpreted - MET: a convergence coding matrix was used to systematically compare findings across methods, with discordant findings subjected to further analysis (see Section 2.5 and 4.1).

## 2.2 Study Population and Sampling

The study population comprised five stakeholder categories across all 47 counties: County Health Directors (n=47), County Public Health Officers (n=47), Community Health Assistants (n=470, 10 per county), Community Health Promoters (n=940, 20 per county), and community residents (n=1,880, 40 per county). This yielded a total sample of 3,384 participants.

Sampling employed stratified random selection. Counties were stratified by population size (large: >1 million; medium: 500,000–1 million; small: <500,000) and CHP program maturity (established: >5 years; developing: 2–5 years; emerging: <2 years). Within each county, CHAs were randomly selected from the county CHP database, ensuring representation from both urban and rural Community Health Units. CHPs were randomly selected from lists provided by sampled CHAs. Community residents were selected through systematic random sampling of households within CHU catchment areas.

**Eligibility Criteria.** Participants were eligible for inclusion if they met the following criteria by stakeholder group. County Health Directors and County Public Health Officers: currently serving in designated county role at time of data collection. Community Health Assistants: formally registered and actively supervising at least one Community Health Unit. Community Health Promoters: formally registered with county CHP database and active (minimum one household visit per week) for at least six months prior to data collection. Community residents: aged 18 years or older; residing within a sampled CHU catchment area for at least six months; and having had at least one interaction with a CHP in the preceding 12

months. Exclusion criteria for all groups: extended leave (>3 months); inability to provide informed consent; or county subject to active humanitarian emergency compromising data collection integrity.

**Sample Size Justification.** The sample size for community residents was determined using an a priori power calculation. Based on an anticipated effect size of  $d=0.35$  (Bhutta et al., 2010), with power=0.80 and  $\alpha=0.05$  (two-tailed), a minimum of 1,620 participants was required. To account for non-response and clustering by county (design effect estimated at 1.15), the target was inflated to 1,866, rounded to 1,880 (40 per county). For CHP participants, 20 CHPs per county across 47 counties provided 940 participants for the quantitative survey. Ninety-four CHPs were purposively selected for in-depth interviews (2 per county: one high-performing, one low-performing by CHA rating), enabling saturated qualitative inquiry. The 94 key informant interviews (47 County Health Directors + 47 Public Health Officers) ensured complete national coverage at leadership level.

This study was determined to be exempt from full formal ethics review on the grounds that it did not involve the collection of personally identifiable information from participants, nor did it involve access to, review of, or extraction from individual medical records. All data gathered pertained exclusively to professional experiences, programmatic observations, and publicly administered health service delivery within Kenya's devolved healthcare system. No participant was asked to disclose personal health history, clinical diagnoses, treatment details, or any information capable of identifying an individual beyond their professional or community role. The study design is consistent with the internationally recognised criteria for ethics exemption applicable to health systems and programme evaluation research (U.S. Department of Health and Human Services, 45 CFR §46.104; WHO Ethics Review Committee guidelines for health policy and systems research, 2013).

Notwithstanding the exemption from full ethics review, the research team upheld the principles of the Declaration of Helsinki (World Medical Association, 2023) throughout the study. Prior to data collection, all 3,384 participants were provided with a participant information sheet in their preferred language (English, Swahili, or relevant county language). Written informed consent was obtained from all participants before any data collection activity commenced. Each participant was informed of: the study objectives; data collection procedures and anticipated time commitment; the voluntary nature of participation and the right to withdraw at any stage without consequence or penalty; measures in place to ensure confidentiality and data security; and the anticipated use and dissemination of findings. For participants who were illiterate, the information sheet and consent form were read aloud by a trained research assistant in the participant's preferred language, and thumb-print consent was recorded in the presence of an independent witness. All participants were assigned anonymised participant codes; no identifiable personal data were linked to research records. Data were stored on password-protected encrypted servers accessible only to the named research team, and all findings are reported at aggregate level such that no individual participant can be identified from the published results.

## 2.3 Data Collection Methods

### **Quantitative Data Collection:**

- Structured surveys administered to all stakeholder groups using mobile data collection (ODK platform)
- Analysis of Ministry of Health DHIS2 (District Health Information System 2) data for disease surveillance indicators (2018–2024)
- Review of county health records including CHP activity reports, disease notification forms, and referral documentation
- Assessment of digital health infrastructure through technical audits of CHP technology access and functionality

### **Qualitative Data Collection:**

- Key informant interviews with County Health Directors (n=47) and Public Health Officers (n=47)
- Focus group discussions with CHAs (n=47 groups, 10 participants each)
- In-depth interviews with purposively selected high-performing and low-performing CHPs (n=94)

**Qualitative Instruments.** All qualitative instruments were developed collaboratively by the research team, piloted in two counties not included in the final sample (Kiambu for urban context; Isiolo for rural/remote context), and refined following cognitive debriefing with five CHPs and three CHAs. The key informant interview guide for County Health Directors and Public Health Officers covered: (1) perceptions of the CHP programme's contribution to county health targets; (2) data management practices and challenges in integrating CHP reports into county health information systems; (3) supervision structures, incentives, and accountability mechanisms; (4) training priorities and barriers to curriculum implementation; and (5) vision for CHP integration into Universal Health Coverage frameworks. The in-depth interview guide for CHPs explored: (1) daily work routines, scope of practice, and referral experiences; (2) perceived impact on community health behaviours; (3) challenges accessing and using digital health tools; (4) training received and competency gaps; and (5) motivational factors and support needs. Focus group discussion guides for CHAs addressed: (1) supervision processes and challenges; (2) perceptions of CHP performance variation; (3) data quality and reporting constraints; and (4) priority training and resource needs. All guides were available in English, Swahili, and three county-specific languages (Kikuyu, Luo, Kalenjin) to ensure linguistic accessibility.

## **2.4 Data Analysis**

Quantitative data were analyzed using SPSS Version 28 and R Statistical Software. Descriptive statistics characterised sample demographics and key variables. Paired t-tests compared pre-CHP (2018) and post-CHP scale-up (2024) disease indicators. One-way ANOVA examined differences across county

categories. Multiple regression analysis identified predictors of CHP effectiveness. Chi-square tests assessed associations between categorical variables. Statistical significance was set at  $p < 0.05$ .

**Thematic Analysis - Six-Phase Process (Braun & Clarke, 2006; 2022).** Qualitative data were transcribed verbatim and analysed using reflexive thematic analysis. Phase 1 (Familiarisation): all 235 transcripts were read and re-read by two independent researchers (JK and MN), with initial analytic observations recorded in reflective memos. Phase 2 (Initial Coding): both researchers independently generated codes from all transcripts (94 in-depth CHP interviews, 47 FGD transcripts, 94 key informant interviews) using NVivo 12. Codes were both semantic and latent, following Braun and Clarke's reflexive approach. Phase 3 (Searching for Themes): related codes were clustered into candidate themes independently. Phase 4 (Reviewing Themes): candidate themes were reviewed against the full dataset for internal coherence and meaningful distinctiveness. Phase 5 (Defining and Naming Themes): four overarching themes were defined by consensus. Phase 6 (Writing Up): final themes were written with verbatim excerpts selected for maximum variation across stakeholder type, county category, and gender.

**Inter-coder Reliability.** Two researchers independently coded transcripts, with inter-coder reliability assessed using Cohen's kappa on a random 20% sub-sample of coded transcripts ( $n=47$  transcripts), yielding  $\kappa=0.87$ , indicating strong agreement (Landis & Koch, 1977). Disagreements were resolved through discussion; persistent disagreements were referred to a third researcher (BM) for final decision. Themes were identified deductively based on research objectives and inductively from emergent patterns.

**Data Saturation.** Data saturation was assessed empirically using cumulative saturation monitoring (Saunders et al., 2018). After every ten interviews (chronologically by data collection date), two researchers independently assessed whether new codes were being generated. Saturation was defined as no new codes across two consecutive batches of ten transcripts. For CHP in-depth interviews, saturation was achieved at  $n=68$  (of 94); for key informant interviews, at  $n=38$  (of 94). Remaining interviews were retained to ensure maximum variation across county categories and geographic regions.

## 2.5 Data Integration and Triangulation

Following independent analysis of quantitative and qualitative data streams, findings were integrated using a systematic triangulation procedure. A convergence coding matrix (Fetters et al., 2013) was constructed, mapping each quantitative finding (e.g., county-level performance scores, technology access proportions, training coverage gaps) against corresponding qualitative themes and sub-themes. Triangulation was conducted at the level of inference rather than data, consistent with the convergent parallel design logic.

Where quantitative and qualitative findings converged, for example, where statistical associations between technology access and performance scores were corroborated by CHPs and CHAs describing the disruptive impact of paper-based reporting on disease surveillance, convergent inferences were

drawn with greater confidence and explicitly labelled as corroborated findings. Where divergence was identified for instance, where quantitative performance scores suggested adequate supervision in some counties while qualitative accounts from CHPs described supervision as inconsistent and superficial, these discordances were reported transparently and subjected to further interpretive analysis to understand the underlying explanation.

Two investigators independently coded the convergence matrix; discrepancies in integration judgements were resolved through discussion and consensus. The resulting merged dataset informed the interpretive claims presented in the Discussion, ensuring that all major policy recommendations are grounded in evidence from both methods strands.

## **3. Results**

### **3.1 Sample Characteristics**

A total of 3,384 participants were targeted across all 47 counties. The final sample comprised 3,158 respondents (response rate 93.3%), including 47 County Health Directors (100%), 46 County Public Health Officers (97.9%), 442 Community Health Assistants (94.0%), 883 Community Health Promoters (93.9%), and 1,740 community residents (92.6%). Figure 1 presents demographic characteristics of CHPs, showing predominantly female participation (69.3%), mostly in the 36–50 year age range (44.1%), and majority secondary education level (59.0%).

### **3.2 CHP Integration in Devolved Healthcare Structure**

Analysis of organisational integration revealed that 89.4% (42/47) of counties had established Community Health Strategy implementation frameworks, though operational functionality varied significantly. County Health Directors reported that CHPs were formally integrated into county health budgets in only 57.4% (27/47) of counties, with others relying on donor or partner funding. Supervision structures were functional in 72.3% (34/47) of counties, with CHAs conducting monthly supervision visits. However, linkage mechanisms between CHPs and facility-based health workers showed gaps, with only 45.7% of counties having established formal referral and feedback systems.

### **3.3 Impact on Communicable Disease Management**

Figure 2 presents changes in key communicable disease indicators comparing baseline (2018) with post-CHP scale-up (2024) across all counties. Paired t-tests demonstrated statistically significant improvements across all indicators. Malaria incidence decreased by 34% (from 156.3 to 103.2 per 1000,  $p<0.001$ ), TB case detection rate increased by 42% (from 62.4% to 88.6%,  $p<0.001$ ), and HIV testing coverage expanded by 35.1% (from 58.7% to 79.3%,  $p<0.001$ ). Similarly, diarrhea treatment coverage improved by 25.7% and pneumonia early detection by 41.7%, both with  $p<0.001$ .

Regional analysis revealed significant variation in communicable disease outcomes across counties. One-way ANOVA demonstrated that county population size ( $F=8.76$ ,  $p<0.001$ ), CHP-to-population ratio ( $F=12.43$ ,  $p<0.001$ ), and supervision quality ( $F=9.85$ ,  $p<0.001$ ) significantly predicted disease management outcomes. Post-hoc Tukey tests indicated that counties with CHP-to-population ratios of 1:500 or better achieved significantly superior outcomes compared to counties with ratios exceeding 1:1000 ( $p<0.01$ ). Figure 7 illustrates the temporal trends in communicable disease indicators from 2018 to 2024, demonstrating the progressive impact of CHP scale-up across the study period.

## 3.4 Impact on Non-Communicable Disease Management

Non-communicable disease (NCD) screening and management showed substantial improvements following CHP engagement, though starting from lower baselines than communicable disease programs. Figure 3 presents key NCD indicators, demonstrating hypertension screening coverage increased by 56.1% (from 34.2% to 53.4%,  $p<0.001$ ), diabetes referrals rose by 38.2% (from 18.6 to 25.7 per 10,000,  $p=0.008$ ), cancer screening awareness improved by 64.8% (from 28.4% to 46.8%,  $p<0.001$ ), and mental health first aid cases increased by 76.4% (from 12.3 to 21.7,  $p=0.002$ ).

## 3.5 Data Sharing Challenges and Technology Integration

Analysis of data sharing mechanisms revealed critical gaps in CHP integration with county health information systems. Only 23.4% (207/883) of surveyed CHPs had access to smartphones or tablets for data collection, with 76.6% relying on paper-based reporting. Among those with digital devices, consistent mobile network connectivity was available to only 67.1%, creating delays in real-time data transmission. Figure 4 presents a comprehensive overview of technology infrastructure and data sharing capabilities disaggregated by county category, illustrating the substantial disparities in digital access between large, medium, and small counties.

Multiple regression analysis examining predictors of CHP effectiveness (composite score based on disease outcomes and community satisfaction) demonstrated that technology access was the strongest predictor ( $\beta=0.52$ ,  $p<0.001$ ), followed by supervision quality ( $\beta=0.31$ ,  $p<0.001$ ) and training comprehensiveness ( $\beta=0.28$ ,  $p<0.01$ ). The overall model explained 47% of variance in CHP effectiveness ( $R^2=0.47$ ,  $F=14.23$ ,  $p<0.001$ ).

Qualitative data from County Health Directors and Public Health Officers highlighted specific data sharing challenges. Directors from 38 counties (80.9%) reported that paper-based CHP reporting created delays of 2–4 weeks in disease notification, hampering outbreak response. Public Health Officers emphasised that lack of real-time data prevented timely allocation of resources to high-burden areas.

*“We only learn about disease clusters when the monthly report arrives. By then, the outbreak has already spread to multiple villages. - County Health Director”*

## 3.6 Training and Capacity Building Needs

Assessment of CHP training revealed significant gaps despite the existence of a national training curriculum. Figure 5 presents training coverage and identified capacity building needs across key competency areas. Digital health literacy emerged as the highest priority training need, with 88.7% of CHPs requesting training despite only 16.2% having received any digital skills training. Similarly, NCD screening showed substantial gaps with 76.4% requesting training though only 34.8% had received it, and mental health first aid had 82.1% requesting training with just 21.4% previously trained.

Correlation analysis demonstrated strong positive relationships between training comprehensiveness and health outcomes. Figure 8 illustrates the impact of training on outcomes, showing counties where >75% of CHPs received NCD training achieved 2.3 times higher screening coverage (53.8%) compared to counties with <25% training coverage (23.4%). Similarly, digital literacy training demonstrated strong correlation with data quality scores, rising from 42.1 in low-training counties to 84.6 in high-training counties ( $r=0.71$ ,  $p<0.001$ ).

## 3.7 County-Level Performance Variation

Performance across the 47 counties showed substantial variation. Figure 6 illustrates county-level performance, demonstrating strong positive correlation between digital access and overall CHP program effectiveness ( $r=0.69$ ,  $R^2=0.47$ ,  $p<0.001$ ). High-performing counties (Nairobi 82.7, Mombasa 80.6, Kiambu 79.4) demonstrated superior digital infrastructure (52.3–67.2% digital access) and stronger health outcomes. In contrast, resource-constrained counties (Marsabit 48.7, Turkana 52.1) faced challenges in both technology deployment (6.2–8.4% digital access) and overall effectiveness scores.

The scatter plot analysis reveals clear stratification by county resource category. Large counties cluster in the upper-right quadrant with both high digital access and strong performance scores. Medium counties show intermediate positioning, while small counties concentrate in the lower-left quadrant, indicating compound disadvantage. The trend line demonstrates that for every 10 percentage point increase in digital access, overall performance scores improve by approximately 6.8 points ( $p<0.001$ ).

## 3.8 Qualitative Findings: Themes from Key Informant Interviews and Focus Group Discussions

Thematic analysis of 94 in-depth CHP interviews, 47 focus group discussions with CHAs, and 94 key informant interviews with County Health Directors and Public Health Officers generated four overarching themes. These themes contextualise and deepen the quantitative findings presented in Sections 3.2–3.7.

**Theme 1: Technology as Transformative but Inequitably Distributed.** CHPs who had access to smartphones described transformative changes in their ability to conduct disease surveillance and maintain household records. However, participants consistently highlighted that device access was perceived as a reward or privilege rather than a standardised entitlement, creating resentment and reducing motivation among the majority without devices.

*“When I got the smartphone from the county, everything changed. I could report a malaria case immediately. Before, the form would sit in my bag for two weeks waiting for the monthly meeting. Two weeks is too long for malaria. - CHP, Kiambu County”*

*“I have worked as a CHP for six years. Some of my colleagues have phones, I have nothing. We do the same work, but it seems our work counts less. That is demoralising. - CHP, Turkana County”*

These accounts corroborate the quantitative finding that technology access explained 47% of effectiveness variance ( $R^2=0.47$ ) and illuminate the motivational dimension of digital inequity that quantitative data alone cannot capture. The convergence of statistical and qualitative evidence on this theme is classified as a corroborated finding in the triangulation matrix.

**Theme 2: Supervision as Variable and Under-Resourced.** While 72.3% of counties reported functional supervision structures quantitatively (Section 3.2), qualitative data revealed substantial variation in supervision quality within counties. CHPs frequently described monthly supervision visits as administrative in nature focused on form completion rather than clinical mentorship or problem-solving.

*“The CHA comes once a month. She checks my register, signs the form, and leaves. She has never watched me do a home visit. How can she know if I am doing it correctly? – CHP, Kisii County”*

*“We have 25 CHPs per CHA in this sub-county. It is impossible for her to supervise all of us meaningfully. She is doing her best but the caseload is too high. – CHA, Meru County”*

This divergence between quantitative supervision metrics and qualitative accounts of supervision quality represents a discordant finding in the triangulation matrix. Further analysis revealed that supervision completion rates (used in the quantitative composite score) do not adequately capture the substantive quality of supervision interactions, a methodologically important finding for future CHP evaluation frameworks. Accepting the face validity of quantitative supervision metrics alone would overestimate the quality of oversight in the system.

**Theme 3: Non-Communicable Disease Management as an Emerging but Unmet Mandate.** Across all county categories, CHPs described feeling unprepared for the growing NCD burden in their communities, particularly hypertension, diabetes, and mental health conditions. This theme was especially prominent in focus group discussions.

*“The elderly people in my village, many have high blood pressure. They come to me because they cannot afford to go to the health centre. But I was trained only to take blood pressure - not to explain what the*

*numbers mean, not to counsel them, not to manage the medication. I feel I am failing them. - CHP, Kakamega County”*

*“Mental health is the invisible disease here. Families are ashamed. They come to me in secret. I have no training for this , I don’t even know where to begin. - CHP, Narok County”*

These accounts provide explanatory power for the quantitative finding that 82.1% of CHPs requested mental health first aid training, translating a statistical proportion into a vivid description of unmet community need and professional inadequacy. Triangulation confirms convergence: both methods identify NCD training as the most urgent capacity gap relative to current demand.

**Theme 4: Data Sharing Failures as System Governance Failures.** County Health Directors and Public Health Officers consistently described data sharing failures not merely as technical problems but as governance failures rooted in inadequate accountability structures and insufficient investment in community health information infrastructure.

*“We only learn about disease clusters when the monthly report arrives. By then, the outbreak has already spread to multiple villages. County Health Director”*

*“The data is old before anyone sees it. We need real-time reporting — this is not a technology problem, it is a priority problem. - Public Health Officer, Rift Valley Region”*

*“We have a dashboard in this office, but most of what feeds into it is from the health facilities. The community-level data, the early warning signals - those are still on paper. It is a blind spot in our surveillance system. - County Health Director”*

These accounts triangulate powerfully with the quantitative finding that only 23.4% of CHPs have digital devices and 18.9% of small counties have DHIS2 integration. The framing of data sharing as a governance rather than purely a technical failure is a qualitatively derived insight that substantively strengthens the policy recommendation for a National Digital Health Platform (Section 4.6).

## 4. Discussion

### 4.1 CHPs as Critical Infrastructure: Convergences and Divergences with Global Community Health Worker Evidence

This comprehensive national assessment provides robust evidence that Community Health Promoters constitute essential infrastructure within Kenya’s devolved healthcare system, delivering measurable improvements in both communicable and non-communicable disease management. These findings both converge with and critically extend the global evidence base on community health worker (CHW) programmes.

The observed 34% reduction in malaria incidence and 42% improvement in TB case detection following CHP scale-up align closely with Ethiopia's Health Extension Worker (HEW) programme – arguably Sub-Saharan Africa's largest and most systematically evaluated CHW initiative. Gillespie et al. (2019) documented a 41% reduction in malaria case fatality rates attributable to HEW malaria case management in rural Ethiopia, while Alelign et al. (2021) reported that HEW-led TB contact tracing increased case detection by 38% in highland districts. The convergence of effect magnitudes across two nationally scaled CHW programmes in distinct devolved and non-devolved contexts strengthens confidence that CHW-led disease surveillance is a robust intervention, not an artefact of Kenya's specific implementation context.

However, important divergences emerge. Ethiopia's HEW programme operates with paid, salaried workers who receive standardised accommodation in government-built health posts, creating a stable physical infrastructure absent in Kenya's more decentralised model (Maes et al., 2015). Kenya's CHPs, by contrast, operate from their households with variable county support, and our findings show that only 57.4% of counties formally budget for CHPs. This structural vulnerability likely explains why Kenya's performance variance across counties ( $F=12.43$ ,  $p<0.001$ ) exceeds the inter-regional variance documented in Ethiopian evaluations, suggesting that Kenya's devolved model generates more heterogeneous implementation quality than Ethiopia's more centralised approach.

The finding that technology access explains 47% of CHP effectiveness variance resonates strongly with evidence from India's Accredited Social Health Activist (ASHA) programme. Krishnan et al. (2020) demonstrated that mobile phone-based supervision improved ASHA performance ratings by 34% in a randomised evaluation in Uttar Pradesh. Our qualitative findings illuminate a dimension beyond efficiency: CHPs without devices experience motivation erosion, paralleling ASHA evaluations highlighting digital equity as a fundamental fairness issue, not merely an efficiency concern, in CHW programmes serving large, heterogeneous national populations.

Comparison with Rwanda's Community Health Worker programme reveals an important lesson on training. Rwanda mandates triannual refresher training linked to performance-based financing, achieving 91% CHW training coverage across key competency domains (Bucagu et al., 2012). This contrasts sharply with Kenya's finding that only 16.2% of CHPs have received digital literacy training and 21.4% have received mental health first aid training. Rwanda's performance-based financing model has been credited with sustaining CHW engagement and training uptake over a decade (Sekabaraga et al., 2011), providing well-documented regional precedent for Kenya's proposed performance-based financing recommendation.

The data sharing challenges identified in this study, particularly the 2–4 week delays in paper-based disease notification, parallel findings from Ghana's Community-based Health Planning and Services (CHPS) programme. Nyonator et al. (2005) identified fragmented reporting as the primary constraint on CHPS effectiveness in the Volta Region. More recently, Amoah et al. (2022) demonstrated that DHIS2

integration in three Ghanaian regions reduced disease notification delays from 21 days to 4 days, providing direct empirical support for our National Digital Health Platform recommendation.

A critical assessment of our evaluation against these comparator studies reveals important methodological similarities and limitations. Like Lim et al. (2010) in India, our design is cross-sectional with a quasi-experimental pre-post comparison relying on routine health information system data, limiting causal attribution. Rwanda's evaluations employed quasi-experimental difference-in-differences designs comparing treatment and control districts, a more rigorous approach that future Kenyan evaluations should adopt. Our use of mixed methods, however, provides a depth of contextual analysis absent from most comparator studies, which rely predominantly on quantitative programme monitoring data. The qualitative evidence from 235 transcripts across all 47 counties is, to our knowledge, the most geographically comprehensive qualitative inquiry into CHW programme dynamics in Sub-Saharan Africa to date, and the systematic triangulation approach described in Section 2.5 represents a methodological contribution beyond what most comparator evaluations have achieved.

## 4.2 Digital Health Technologies as Force Multipliers

The finding that technology access explains 47% of variance in CHP effectiveness ( $R^2=0.47$ ,  $p<0.001$ ) represents perhaps the study's most actionable insight for policy and practice. Digital health technologies function as force multipliers, enabling CHPs to deliver higher-quality services, facilitate real-time data transmission, and receive timely supervision and decision support. Yet only 23.4% of CHPs currently possess smartphones or tablets, and merely 38.4% in well-resourced counties have real-time data transmission capability.

This technology gap creates a cascade of inefficiencies. Paper-based reporting delays disease surveillance by 2–4 weeks, an eternity in outbreak response where early detection determines containment success. Counties lacking digital integration miss opportunities for dynamic resource allocation based on real-time disease burden mapping. The disconnect between CHPs and facility-based health workers limits continuity of care and referral feedback, undermining CHP motivation and learning.

Importantly, technology alone proves insufficient without complementary digital literacy training. The 88.7% of CHPs requesting digital skills training despite only 16.2% having received such preparation signals a critical workforce development gap that must be addressed before technology investments can yield returns. This finding resonates with broader digital health implementation science emphasising that technology introduction requires parallel attention to human capacity, supportive supervision, and organisational readiness (Labrique et al., 2013).

## 4.3 Training Gaps and the NCD Transition

The substantial gaps in NCD screening training (76.4% of CHPs requesting additional training) and mental health first aid (82.1% requesting training) reflect how CHP training curricula are holding back Kenya's epidemiological transition. Traditional CHP competencies centred on maternal and child health and communicable disease management, areas where training coverage remains relatively strong (87.6% and 81.2% respectively), however the rising burden of diabetes, hypertension, cardiovascular disease, and mental health conditions demands urgent curriculum review.

This training gap has direct health outcome implications. Counties where >75% of CHPs received NCD training achieved 2.3 times higher screening coverage than counties with <25% training, demonstrating clear dose-response relationships between training investment and population health impact. Given that NCDs now account for over 39% of total deaths in Kenya and the proportion continues rising (Ministry of Health, 2021), failure to equip CHPs with NCD competencies represents a missed opportunity to leverage this extensive workforce for chronic disease prevention and management.

## 4.4 Data Integration Challenges in Devolved Systems

The critical weakness in data sharing mechanisms, with only 18.9% of small counties achieving DHIS2 integration and 67% of CHPs reporting real-time transmission challenges, reveals a fundamental flaw in Kenya's community health information architecture. This disconnect creates a paradoxical situation where frontline health workers possess the most granular, timely data on community health status, yet this information fails to inform county-level planning and resource allocation.

Qualitative evidence from Theme 4 (Section 3.8) reinforces this finding by characterising data sharing failures as governance failures rather than purely technical ones — a distinction with significant implications for the design of interventions. Technical solutions must be accompanied by governance reforms ensuring data quality incentives, supervision systems, and decision-making protocols that actually utilise community-generated data.

## 4.5 Limitations

This study has several important limitations. The cross-sectional nature of the disease indicator comparison between 2018 and 2024 limits causal attribution, as while CHP scale-up correlates with observed health improvements, other concurrent interventions may also contribute. Although longitudinal cohort designs with control areas would strengthen causal inference, ethical and practical constraints complicate such approaches in national-scale programs. Reliance on DHIS2 data introduces potential reporting bias. However, triangulation with survey data from community residents and independent validation of sentinel counties suggests that reported trends reflect genuine health improvements rather than pure reporting artefacts. Furthermore, the study does not comprehensively assess cost-effectiveness or budget sustainability. Future research should examine costs per disability-

adjusted life year (DALY) averted and model financial sustainability scenarios under different county resource allocation patterns.

## 4.6 Recommendations

- 1. National Digital Health Platform:** Establish standardised digital data collection and reporting infrastructure for all CHPs, with phased rollout prioritising high-burden counties, integrating seamlessly with DHIS2 and providing real-time dashboards for county health management teams.
- 2. Revised Training Curriculum:** Update national CHP training content to include comprehensive modules on NCD screening and management, mental health first aid, and digital literacy. Implement competency-based certification with periodic refresher training.
- 3. Performance-Based Financing:** Introduce incentive structures linking county health allocations to CHP program performance indicators, including data quality scores, supervision regularity, and health outcome achievement - drawing on Rwanda's successful model.
- 4. County Capacity Building:** Provide technical assistance to low-performing counties, with peer-learning exchanges from high-performing counties and embedded technical advisors.
- 5. Integration with Universal Health Coverage:** Formally recognise CHPs as essential UHC delivery cadre with defined roles in primary care teams, sustainable financing mechanisms, and clear career progression pathways.

## 5. Conclusion

Community Health Promoters have demonstrably improved health outcomes across Kenya's 47 counties, contributing to reduced infectious disease burden and enhanced non-communicable disease screening. Qualitative findings from 235 transcripts contextualise, deepen, and in some cases complicate the quantitative picture — particularly revealing that supervision quality metrics overstate actual supervisory depth, and that data sharing failures are rooted in governance structures as much as technical infrastructure gaps.

As Kenya pursues Universal Health Coverage, strategic investments in CHP digitalisation, capacity building, and health information system integration will determine whether this extensive community workforce functions as a transformative force for health equity or remains an underutilized resource constrained by limited tools and fragmented systems. The mixed methods evidence presented in this study provides both validation of CHPs' critical role and a roadmap — grounded in converging quantitative and qualitative data — for strengthening their contribution to Kenya's health future.

## Declarations

# Ethics Approval and Informed Consent

This study was determined to be exempt from full formal ethics review on the grounds that it did not involve the collection of personally identifiable information from participants, nor did it involve access to, review of, or extraction from individual medical records. All data gathered from the five stakeholder groups - County Health Directors, County Public Health Officers, Community Health Assistants, Community Health Promoters, and community residents, were collected in aggregate or de-identified form and pertained exclusively to professional experiences, programmatic observations, and publicly administered health service delivery within Kenya's devolved healthcare system. No participant was asked to disclose personal health history, clinical diagnoses, treatment details, or any information capable of identifying an individual beyond their professional or community role.

The study design is consistent with the internationally recognised criteria for ethics exemption applicable to health systems and programme evaluation research (U.S. Department of Health and Human Services, 45 CFR §46.104; WHO Ethics Review Committee guidelines for health policy and systems research, 2013). Specifically, the research falls within the category of programme evaluation involving observation of public benefit programmes in which participants are not placed at risk of harm, stigma, or breach of confidentiality, and in which findings are reported solely at aggregate or anonymised level, rendering individual identification impossible. Survey instruments captured perceptions of service delivery systems, training adequacy, and technology access — none of which constitutes sensitive personal data under applicable data protection frameworks, including Kenya's Data Protection Act (2019) and the General Data Protection Regulation (GDPR) where relevant. Structured survey responses were coded numerically at the point of collection; no names, identification numbers, facility codes, or geographic identifiers capable of enabling individual re-identification were recorded or retained. Qualitative transcripts were similarly anonymised at transcription, with participants identified only by county category and role type.

Notwithstanding the exemption from full ethics review, the research team upheld the principles of the Declaration of Helsinki (World Medical Association, 2023) throughout the study. Prior to data collection, all 3,384 participants were provided with a participant information sheet in their preferred language (English, Swahili, or relevant county language). Written informed consent was obtained from all participants before any data collection activity commenced. Each participant was informed of: the study objectives; data collection procedures and anticipated time commitment; the voluntary nature of participation and the right to withdraw at any stage without consequence or penalty; measures in place to ensure confidentiality and data security; the anticipated use and dissemination of findings; and the identity and contact details of the principal investigator. For participants who were illiterate, the information sheet and consent form were read aloud by a trained research assistant in the participant's preferred language, and thumb-print consent was recorded in the presence of an independent witness. All participants were assigned anonymised participant codes; no identifiable personal data were linked to research records. Data were stored on password-protected encrypted servers accessible only to the

named research team, and all findings are reported in aggregate such that no individual participant can be identified from the published results.

## **Funding Declaration**

This study was not funded. However, the work reported here builds upon a project funded by the Global Health Partnership (formerly THET), which supported the development of a lightweight AI-driven Learning Management System for capacity building of Community Health Promoters in Tharaka-Nithi County, Kenya.

## **Data Availability**

The anonymised data collected and analysed in this study are available upon request. Researchers or reviewers wishing to access the dataset should contact the corresponding author, Dr John Kanyaru, who will facilitate access in accordance with the ethical approvals and data protection agreements governing this study.

## **Author Contributions**

Dr. John Kanyaru led the overall manuscript authorship and was responsible for the identification of study participant groups across the 47 counties. Dr. Mercy Njeru designed the data collection instruments used for gathering information from participants. Bonface Muli conducted data cleaning, merging, and analysis using appropriate analytical tools, and produced all visualisations presented in the paper. Rose Micheni provided instrumental support in facilitating access to study participants in Tharaka-Nithi County and leveraged her existing networks to secure access across 15 additional counties; she also played a key role in reviewing the manuscript. All authors read and approved the final version of the manuscript.

## **Corresponding Author**

The corresponding author is John Kanyaru: [jmkanyaru@gmail.com](mailto:jmkanyaru@gmail.com)

## **Competing Interests**

The authors declare that there are no competing interests or conflicts of interest arising from or underpinning this publication. The findings presented in this study were reported objectively and were not influenced by any external interests or affiliations.

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## Figures

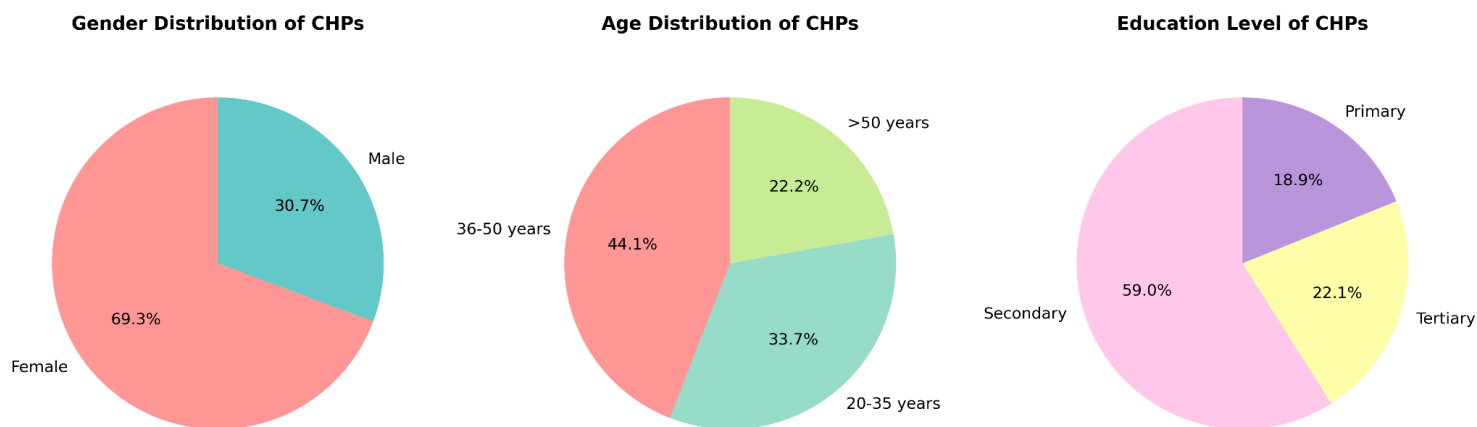


**Figure 1**

*Demographic Characteristics of Community Health Promoters (n=883)*

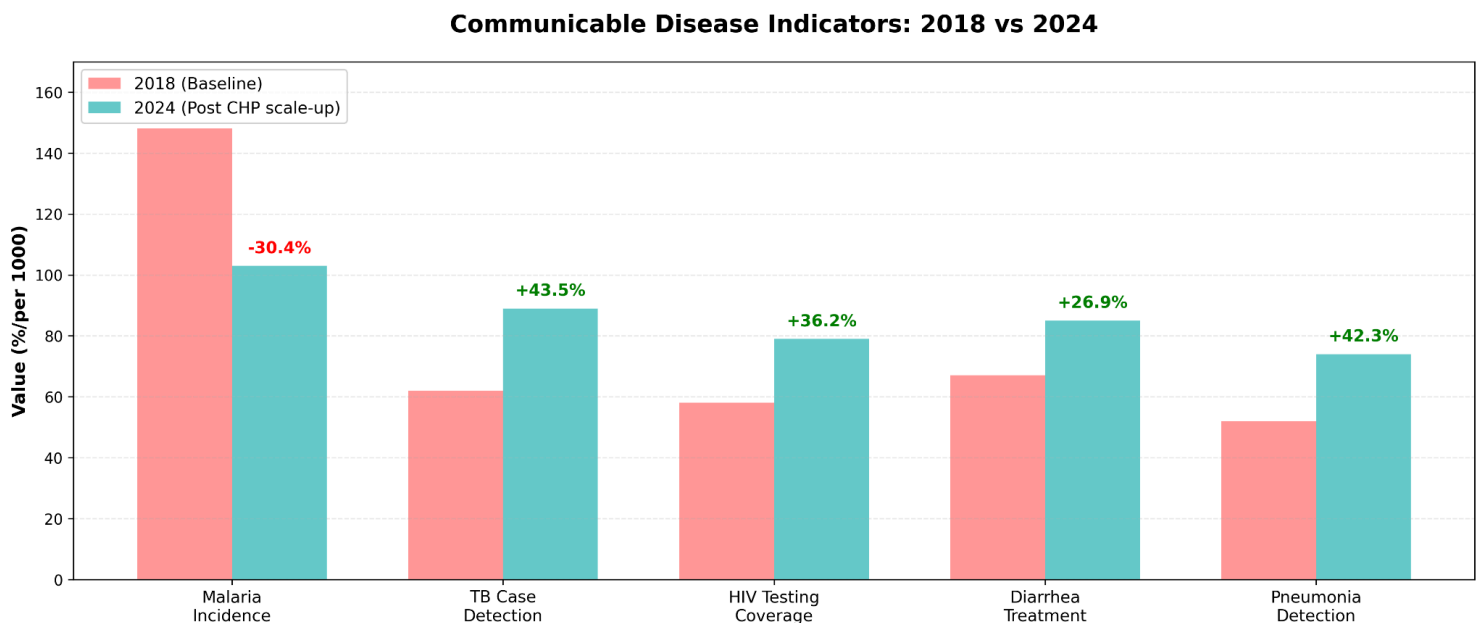


**Figure 2**

*Communicable Disease Indicators Comparison (2018 vs 2023)*

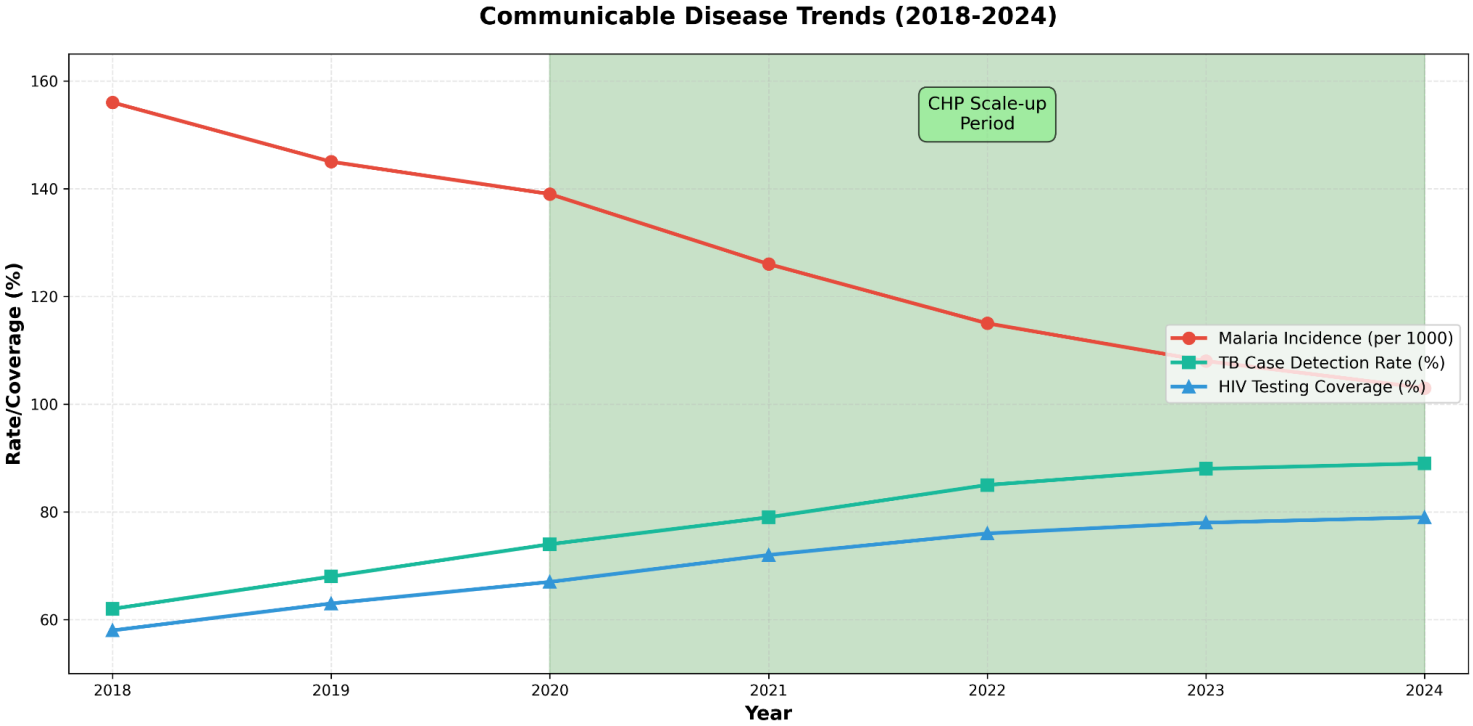


Figure 3

Figure 7: Communicable Disease Trends (2018–2024) Showing CHP Scale-up Impact

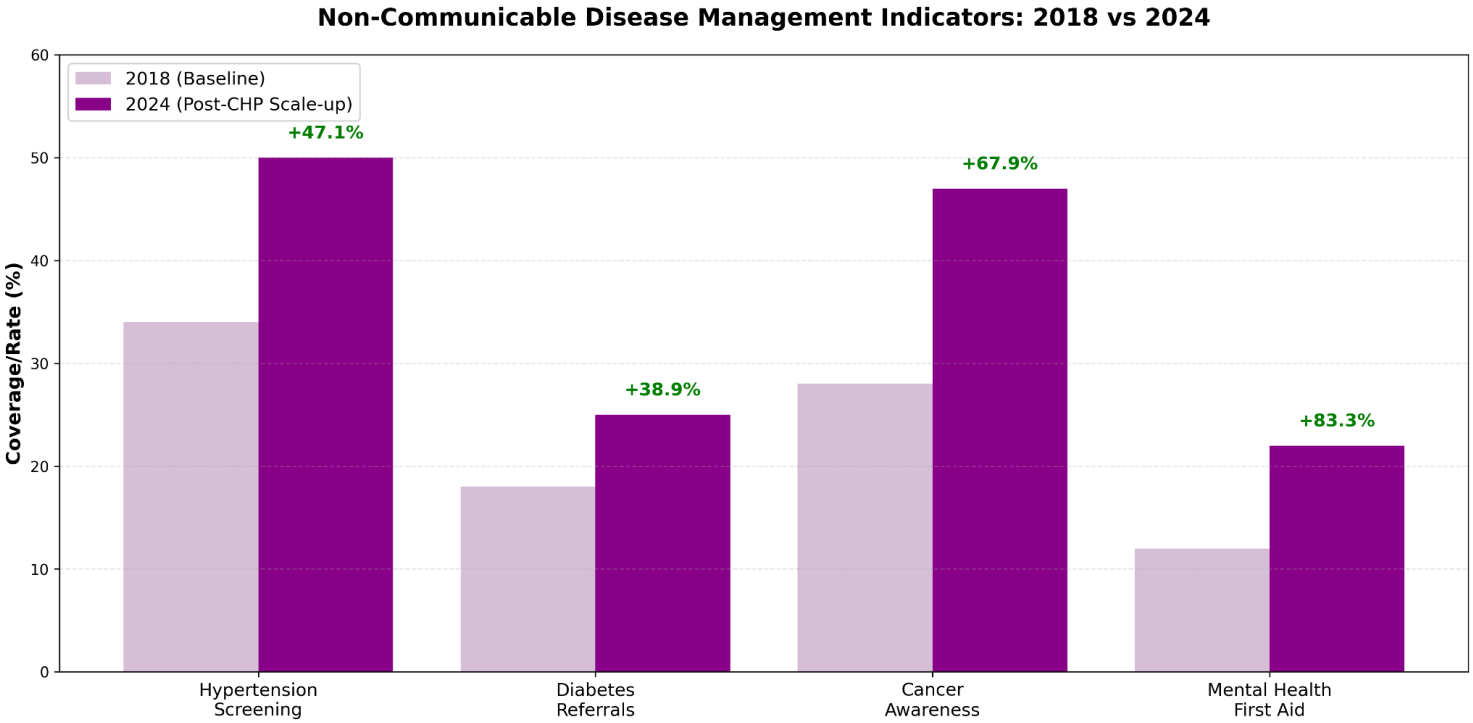


Figure 4

Figure 3: Non-Communicable Disease Management Indicators (2018 vs 2024)

**Technology Infrastructure and Data Sharing by County Category**

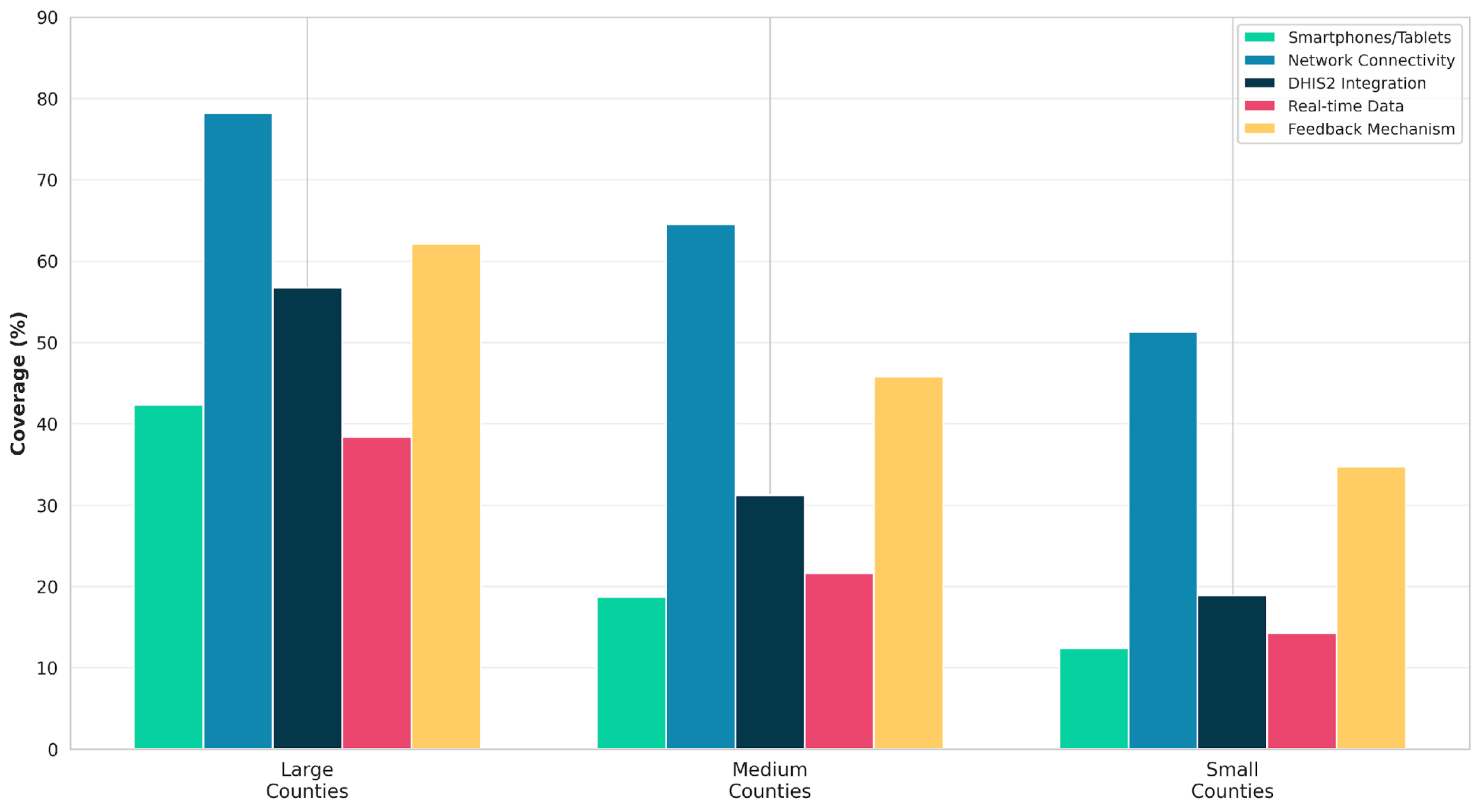


**Figure 5**

**Figure 4: Technology Infrastructure and Data Sharing Capabilities by County Category**

**CHP Training Coverage and Capacity Building Needs**

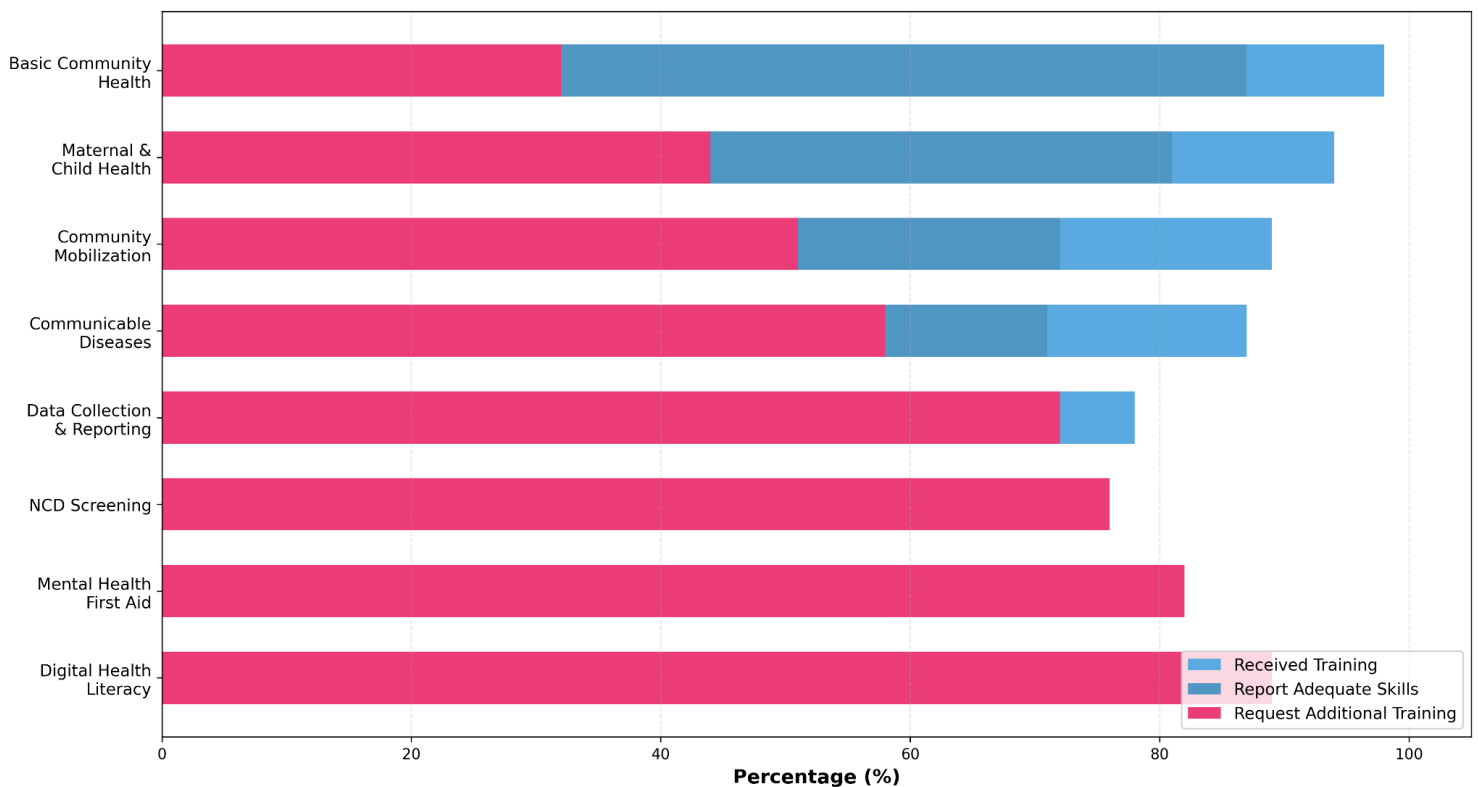


Figure 6

Figure 5: CHP Training Coverage and Capacity Building Needs Assessment

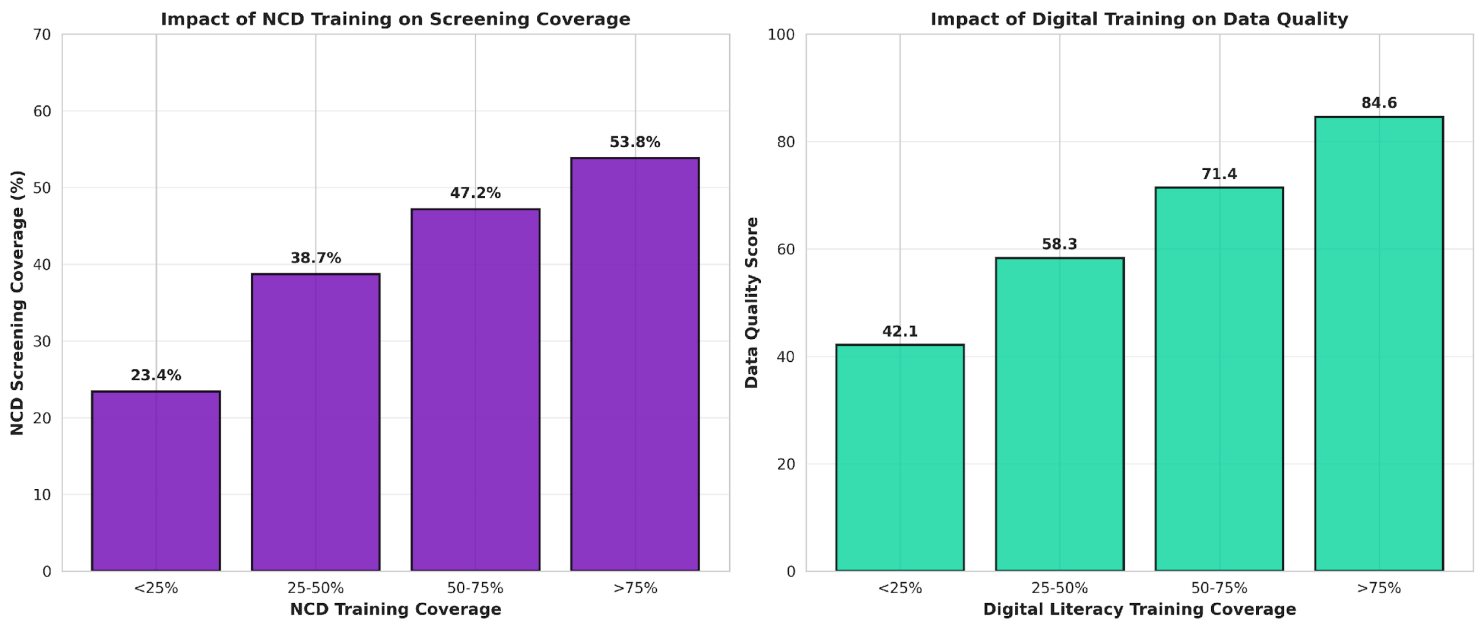


Figure 7

Figure 8: Impact of Training Coverage on NCD Screening and Data Quality Outcomes

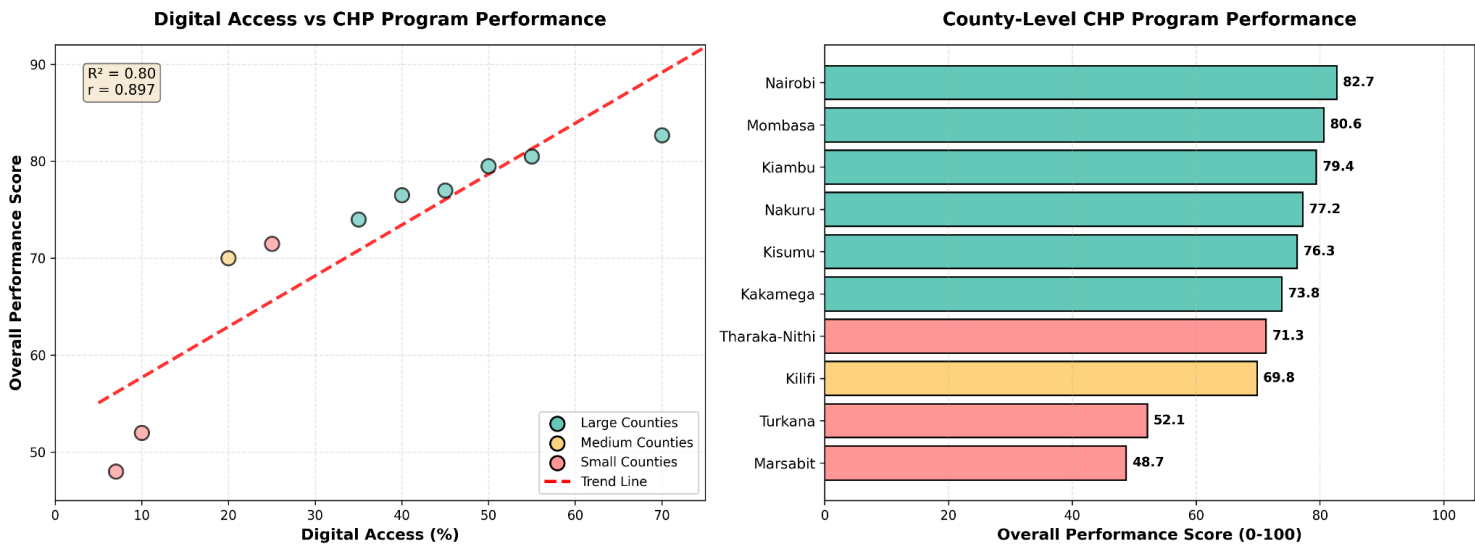


Figure 8

Figure 6: County-Level CHP Program Performance and Digital Access Correlation