RESEARCH ARTICLE

Feasibility, acceptance, and workflow integration of an AI-enabled clinical decision support system for non-communicable diseases in Kiambu County, Kenya: A mixed-methods implementation evaluation

[version 1; peer review: 1 approved with reservations]

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v1 **First published:** 09 Feb 2026, **9**:6
https://doi.org/10.12688/openresafrica.16362.1
Latest published: 09 Feb 2026, **9**:6
https://doi.org/10.12688/openresafrica.16362.1

Abstract

Background

Non-communicable diseases (NCDs), particularly hypertension and diabetes, impose a growing burden on health systems in low- and middle-income countries like Kenya. Artificial intelligence (AI)-driven Clinical Decision Support Systems (CDSS) may enhance diagnostic accuracy and adherence to clinical guidelines, yet their feasibility and acceptability among frontline clinicians in real-world settings remain underexplored.

Methods

We conducted a mixed-methods implementation study in 10 health facilities in Kiambu County, Kenya. The evaluation comprised three components. First, a retrospective review of 1,929 patient records established baseline NCD prevalence and care patterns. Second, we assessed the clinical acceptance of the NCDAI platform, an AI-CDSS

Open Peer Review

Approval Status ?

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version 1 09 Feb 2026	? view

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using a Large Language Model with Retrieval-Augmented Generation, through 300 independent expert physician reviews of its recommendations. Third, we captured clinician perspectives via a cross-sectional Knowledge, Attitudes, and Practices (KAP) survey (n=29) and key-informant interviews (n=11).

Results

The baseline cohort demonstrated a substantial NCD burden: 72.8% had a history of hypertension and 43.1% had diabetes. Expert validation showed high acceptance of AI-generated recommendations, with 67.0% “Agreed,” 26.3% “Partially Agreed,” and only 6.7% “Disagreed,” yielding 93.3% overall (partial or full) agreement. Most disagreements arose in medication and treatment plan recommendations. Clinicians demonstrated strong digital readiness; 86% reported moderate or good IT proficiency, and 69% were already aware of AI in healthcare. Patient-related factors were the most commonly cited barriers to NCD care (33%). Qualitative findings identified operational challenges particularly duplicative data entry arising from parallel paper-based workflows as the main impediment to NCDAI adoption amid high patient volumes.

Conclusions

An AI-driven CDSS for NCD management is feasible and highly acceptable to expert physicians and frontline clinicians in Kenya. The key barrier is not reluctance toward AI but workflow friction. Effective scale-up will require investment in digital infrastructure to enable seamless integration and replacement of paper-based systems.

Keywords
non-communicable disease, clinical decision support, artificial intelligence, Kenya, implementation science, mixed-methods, workflow integration, health systems strengthening.

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Competing interests: No competing interests were disclosed.

Grant information: This work was supported by the Science for Africa Foundation under grant number GC Africa Round 15: Artificial Intelligence (AI) Seed Grant - GCA/SFA/R15/142 awarded to DK and JG.
The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

How to cite this article: Kamau D, Mbugua S, Omondi P *et al.* **Feasibility, acceptance, and workflow integration of an AI-enabled clinical decision support system for non-communicable diseases in Kiambu County, Kenya: A mixed-methods implementation evaluation [version 1; peer review: 1 approved with reservations]** Open Research Africa 2026, **9**:6 https://doi.org/10.12688/openresafrica.16362.1

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Introduction

Kenya, like many nations in sub-Saharan Africa, is navigating a profound epidemiological transition[1]. The burden of disease is rapidly shifting from infectious diseases to non-communicable diseases (NCDs)[2,3]. NCDs now contribute to over half of all hospital admissions and are responsible for 39% of total annual mortality in the country, with cardiovascular diseases being the primary driver[4].

Hypertension and diabetes mellitus represent two of the most significant threats. Nearly one-third of Kenyan adults may be living with hypertension, while diabetes prevalence is estimated at 4.5%[5]. These conditions are often undiagnosed and inadequately managed[6]. The coexistence of diabetes and hypertension, a common comorbidity, significantly amplifies cardiovascular risk and complicates management[7]. This growing burden strains a health system already facing significant resource and workforce constraints[8].

A major challenge in NCD management is ensuring that all patients receive high-quality, evidence-based care consistently[9,10]. The World Health Organization (WHO) has provided a framework through the Package of Essential Noncommunicable (PEN) Disease Interventions, which offers protocols for primary care in low-resource settings[11]. However, translating these guidelines into practice at a busy frontline facility remains difficult. This gap between evidence and practice contributes to poor health outcomes and underscores the need for high-quality health systems[12].

Clinical Decision Support Systems (CDSS) have long been proposed as a method to bridge this gap by providing prompts, reminders, and guideline-based recommendations at the point of care[13]. The advent of powerful, generative Artificial Intelligence (AI) and Large Language Models (LLMs) presents a new opportunity to create more dynamic, responsive, and useful CDSS[14]. These systems can synthesise complex patient data, compare it against a vast knowledge base of medical guidelines, and provide tailored recommendations[15,16]. In settings like Kenya, such tools could enhance diabetes care, guide medication dosing, and provide continuous, on-the-job training for healthcare workers[17–19].

However, the technical feasibility and clinical validity of an AI tool do not guarantee its successful adoption. In real-world clinical settings, tools fail if they are not trusted, are difficult to use, or, most importantly, if they disrupt or add burden to existing clinical workflows. There is a critical implementation gap, and few studies have evaluated the real-world integration of a generative AI-CDSS in frontline African healthcare settings.

This study aimed to evaluate the feasibility, clinical acceptance, and workflow integration of the NCDAI platform, an AI-driven CDSS for hypertension and diabetes management.

Methods

Design and setting

We conducted a mixed-methods implementation study using a sequential exploratory design. The study was implemented in 11 health facilities in Kiambu County, a populous peri-urban county in Kenya. Facilities were purposively selected to represent different tiers of the public health system, including Level 3 health centres and Level 4 and Level 5 hospitals, to ensure variation in patient volume, staffing, and available resources.

The study comprised three integrated components. First, we conducted a retrospective abstraction of patient records to establish baseline characteristics of individuals receiving NCD care. Second, we implemented an expert validation component in which senior physicians reviewed and rated the clinical appropriateness of AI-generated recommendations. Third, we undertook a cross-sectional assessment of frontline clinicians that included a quantitative KAP survey and qualitative key informant interviews (KIIs) to explore usability, acceptability, and implementation barriers.

Inclusion and exclusion criteria

Participants were eligible for inclusion if they were engaged in NCD service delivery or were represented in existing NCD patient records at the participating facilities. Eligible participants included clinicians providing routine hypertension and diabetes care, senior physicians with expertise in NCD management, and patients whose records were available in paper-based or electronic registers during the abstraction period. All participants involved in primary data collection activities provided written informed consent. For the retrospective patient record review, individual patient consent was not required, as all data were fully de-identified prior to analysis in accordance with the approved ethical waiver.

Exclusion criteria included lack of direct involvement in NCD care, incomplete or duplicate patient records, or insufficient demographic or clinical information required for analysis. Individuals directly involved in the development of the NCDAI platform were excluded from expert review activities to minimise potential bias.

Sample size determination

The study employed a purposive sampling strategy to select the county, facilities, and participant groups for each study objective, ensuring that data were collected from stakeholders most relevant to NCD care implementation. For Objective 1, a purposive sample of 1,929 patient records was selected based on availability within the predefined abstraction period and completeness of key variables. For Objective 2, 300 AI-generated case vignettes were reviewed by senior physicians, selected to represent a broad spectrum of clinical presentations. For Objective 3, 29 clinicians participated in the KAP survey, and a purposive subsample of 11 clinicians was selected for KIIs to capture diverse perspectives across facility levels and roles.

Participants and data collection

The study drew data from three participant groups and corresponding data sources: a patient cohort, expert reviewers, and a clinician cohort.

Retrospective patient data were obtained from 1,929 records of individuals receiving hypertension or diabetes care at

the participating facilities. Records were abstracted from paper-based and electronic registers using a standardised abstraction tool. Extracted variables included demographic characteristics, medical and family history, and lifestyle risk factors. All patient records were fully de-identified prior to analysis, in accordance with the approved waiver of consent.

For the expert validation component, 300 patient case vignettes derived from the baseline patient dataset were processed through the NCDAI platform. Each AI-generated recommendation was independently reviewed by a senior physician with expertise in NCD management, who provided agreement ratings and qualitative feedback.

Frontline clinician data were collected from a cohort of 29 medical officers and clinical officers involved in NCD service delivery. All clinicians completed a structured KAP survey administered electronically. A purposive subsample of 11 clinicians participated in in-depth, semi-structured key informant interviews (KIIs), which explored usability, acceptability, and implementation considerations for the NCDAI platform across the facilities.

Intervention

The intervention was the NCDAI platform, an AI-enabled clinical decision support system (CDSS) implemented as a mobile application (Android) and a web-based interface. The platform is powered by a Large Language Model (LLM) operating within a Retrieval-Augmented Generation (RAG) framework, which grounds outputs in a curated knowledge base comprising Kenyan national NCD guidelines and other international evidence-based protocols.

Clinicians received brief, on-site orientation sessions on how to use the platform within routine clinical workflows, including patient registration, history-taking, diagnosis, and management planning. The system was designed to function as a clinical assistant rather than a replacement for clinician judgement. Guardrails were incorporated to ensure that final clinical decisions remained with the clinician, with the AI providing suggested actions and supporting evidence for review.

The platform also incorporated an expert validation module to allow continuous, real-time quality assurance of AI-generated recommendations.

Outcomes

The primary outcomes were feasibility and acceptance of the NCDAI platform. Feasibility was assessed qualitatively through themes emerging from clinician interviews, with a focus on usability, workflow integration, and perceived barriers to adoption. Acceptance was evaluated quantitatively using expert physician agreement ratings of AI-generated recommendations and responses from the clinician KAP survey.

Secondary outcomes included the identification of key implementation barriers and facilitators, thematic characterisation of expert feedback to highlight areas of AI model weakness, and a quantitative description of the baseline NCD burden among patients receiving care at the participating facilities.

Data management

All data collection, handling, and storage procedures followed established ethical and confidentiality standards. Retrospective patient data were abstracted from paper-based and electronic registers using a predefined abstraction tool and entered into a secure digital database hosted on encrypted, password-protected servers. No personal identifiers were extracted; unique study IDs were assigned to all records to ensure anonymity.

Data from clinician surveys and expert reviews were collected electronically using secure, access-controlled survey tools. Qualitative interview recordings were stored in encrypted folders, transcribed verbatim, and de-identified prior to analysis.

Only authorised members of the research team had access to the datasets. Data quality checks including range checks, consistency checks, and verification of missing values were conducted before analysis. All cleaned datasets were backed up on secure institutional servers in accordance with data governance policies.

Data analysis

Quantitative data from the patient record abstraction and the clinician KAP survey were analysed using descriptive statistics. Comparisons of baseline characteristics across facilities were performed using Chi-square tests, with a significance threshold of $p < 0.05$.

All quantitative analyses were conducted using R (version 4.5.1; R Foundation for Statistical Computing).

Qualitative data from the KIIs and the free-text comments from the expert reviews were transcribed and translated where necessary. Analysis followed a thematic framework approach. Two researchers independently coded the transcripts and developed an analytical codebook derived from inductive theme generation. Coding discrepancies were resolved through consensus with a third senior researcher. Dominant themes were identified in relation to usability, clinician confidence, workflow integration, and areas of clinical disagreement. Illustrative quotations were selected to support each thematic category.

Ethical approvals

The study protocol was reviewed and approved by the Mount Kenya University Institutional Scientific and Ethics Review Committee (MKU ISERC, ref: MKU/ISERC/2934). A research license was obtained from the National Commission for Science, Technology and Innovation (NACOSTI, ref: NACOSTI/P/24/38726). All participating clinicians provided written informed consent prior to enrolment in the KAP survey and KIIs. For the retrospective patient record review, a waiver of individual patient consent was granted by the ISERC, as all data were fully de-identified prior to analysis.

Reporting guidance

This manuscript follows established reporting standards aligned with the study's mixed-methods design. The Standards for Reporting Implementation Studies (StaRI) was applied to guide reporting of the implementation and usability evaluation of the NCDAI platform. The STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines were used for the observational components, including the retrospective patient record review and the clinician KAP survey. The COREQ (Consolidated Criteria for Reporting Qualitative Research) checklist informed the reporting of the semi-structured KIIs to ensure transparency in qualitative data collection and analysis.

Results

Baseline patient cohort characteristics

The baseline cohort included 1,929 patients currently engaged in NCD care. Key characteristics are summarized in Table 1. The overall median age was 58.0 years (IQR 46.0–70.0), and the cohort was predominantly female (66.0%, n=1269).

We observed a very high burden of established NCDs. A history of hypertension was present in 72.8% (n=1405) of patients, and 43.1% (n=832) had a history of diabetes. Family history of these conditions was also common, reported by 57.4% for hypertension and 40.4% for diabetes. Lifestyle risk factors were prevalent, with 16.4% reporting alcohol consumption, 14.7% being current or former smokers, and 39.9% reporting no regular physical activity. For all measured characteristics, there was statistically significant variation ($p < 0.001$) in their distribution across the 11 participating facilities.

Expert validation of the NCDAI platform

A total of 300 AI-generated recommendations were independently reviewed by expert physicians. The platform demonstrated high clinical acceptance (Figure 1).

Overall, experts "Agreed" with 67.0% (n=201, 95% CI [61.5%, 72.2%]) of the recommendations. They "Partially Agreed" with 26.3% (n=79, 95% CI [21.4%, 31.7%]) and "Disagreed" with only 6.7% (n=20, 95% CI [4.1%, 10.1%]). This resulted in a total (full or partial) acceptance rate of 93.3% (n=280, 95% CI [89.9%, 95.8%]). This high level of agreement was consistent, though some variation was noted between facilities, with Mary Help Hospital showing very high agreement and Karuri Level 4 showing a higher proportion of "Partial" or "Disagree" responses (additional information is provided in extended data).

Qualitative analysis of expert feedback

Thematic analysis of the free-text comments provided by experts revealed the nature of their agreement and disagreement. The most common themes in comments were related to refining the "Medication and treatment plan," followed by "Diagnostic and baseline recommendations" (e.g., "add ECG," "run HbA1c").

Crucially, analysis of the 99 expert reviews in which full agreement was not achieved (20 Disagree and 79 Partial) showed that disagreements were not random but highly concentrated. The vast majority of both Disagree (15 of 20) and Partial (48 of 79) ratings were linked to recommendations involving medication selection and treatment planning. Additional examples and thematic categories are provided in extended data.

Clinician knowledge, attitudes, and practices

The 29 clinicians participating in the KAP survey had a mean age of 31.2 years, and 55.2% were male. The majority held a Diploma (55.2%) or a Bachelor's degree (31.0%). As shown in Table 2, the cohort demonstrated strong digital readiness. A combined 86% rated their IT proficiency as "Good" (48.3%) or "Moderate" (37.9%). Awareness of AI in healthcare was high at 69.0%, and over half (55.2%) reported having already used AI tools in patient management, most commonly "To seek information about medication" (65.5%).

Perceived barriers and role for AI

When clinicians were asked to identify the greatest challenges in NCD care *before* the intervention, their responses focused on systemic and patient factors, not knowledge gaps. As shown in Figure 2, the most common barrier was "Patient-related issues" (33%), such as non-compliance. This was followed by "Clinical management challenges" (26%), including high patient workload, and "Resource limitations" (19%).

Table 1. Baseline demographic, medical, and lifestyle characteristics of the total patient cohort (N=1929).

Characteristic	Total (N = 1,929)	Gachororo HC (n = 149)	Kiandutu HC (n = 465)	Kihara Level 4 (n = 30)	Mary Help Hospital (n = 833)	Munyu HC (n = 198)	Ngoliba HC (n = 139)	Thika Level 5 (n = 87)	Others (n = 28)	p-value
Age, median (IQR)	58 (46.0–70.0)	57.0 (49.0–70.0)	62.0 (50.0–70.0)	55.5 (49.0–65.0)	56.0 (38.0–70.0)	65.5 (55.0–73.0)	56.0 (47.0–66.0)	57.0 (46.0–64.0)	53.0 (47.0–69.0)	<0.001
Gender, n (%)										<0.001
Female	1,269 (66.0)	116 (77.8)	354 (76.1)	19 (63.3)	467 (56.4)	148 (74.8)	84 (60.4)	62 (71.6)	19 (67.9)	
Male	655 (34.0)	33 (22.2)	111 (23.9)	11 (36.7)	361 (43.6)	50 (25.2)	55 (39.6)	25 (28.7)	9 (32.1)	

The *Others* category comprises hospitals with n < 20.

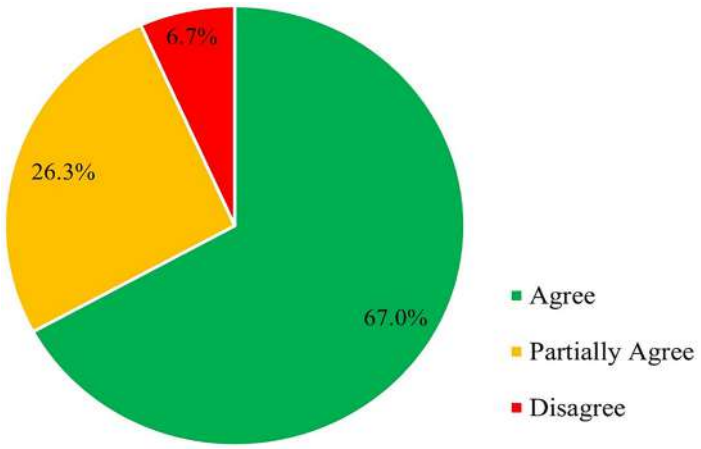

Figure 1. Expert physician agreement with AI-generated recommendations (n=300 reviews). Percentages represent expert physicians' level of agreement with AI-generated clinical recommendations across 300 reviewed scenarios.

Table 2. Characteristics and KAP survey results for participating clinicians (n=29).

Characteristic	Category	n (%)
Age (years), Mean (95% CI)		31.2 (28.1–34.3)
Gender	Male	16 (55.2)
	Female	13 (44.8)
Education level	Diploma	16 (55.2)
	Bachelor's degree	9 (31.0)
	Higher diploma	1 (3.4)
	HND (Family Health)	1 (3.4)
	HND	1 (3.4)
	Master's degree	1 (3.4)
Years of practice	<1 year	5 (17.2)
	1–5 years	9 (31.0)
	5–10 years	6 (20.7)
	>10 years	9 (31.0)
Knowledge score, Mean (95% CI)		5.38 (4.96-5.80)
Attitude score, Mean (95% CI)		4.34 (4.02-4.67)
Practice score, Mean (95% CI)		4.24 (3.94-4.54)

Data are presented as frequencies and percentages unless otherwise indicated. Age is expressed as mean (95% confidence interval), and KAP scores are presented as mean ± standard deviation.

Clinicians' desired roles for AI mirrored these challenges. The most desired function was "Clinical Decision Support" (25.9%) to improve diagnosis and guideline adherence. This was closely followed by a combined 37% who wanted AI to assist with "Data and Information Management" (18.5%) and "Patient Management and Follow-up" (18.5%). Other areas included quality of care and integration (15%), capacity building and training (12%), and other functions (10%). More detailed on clinician-perceived barriers to NCD care and thematic categories is provided in extended data.

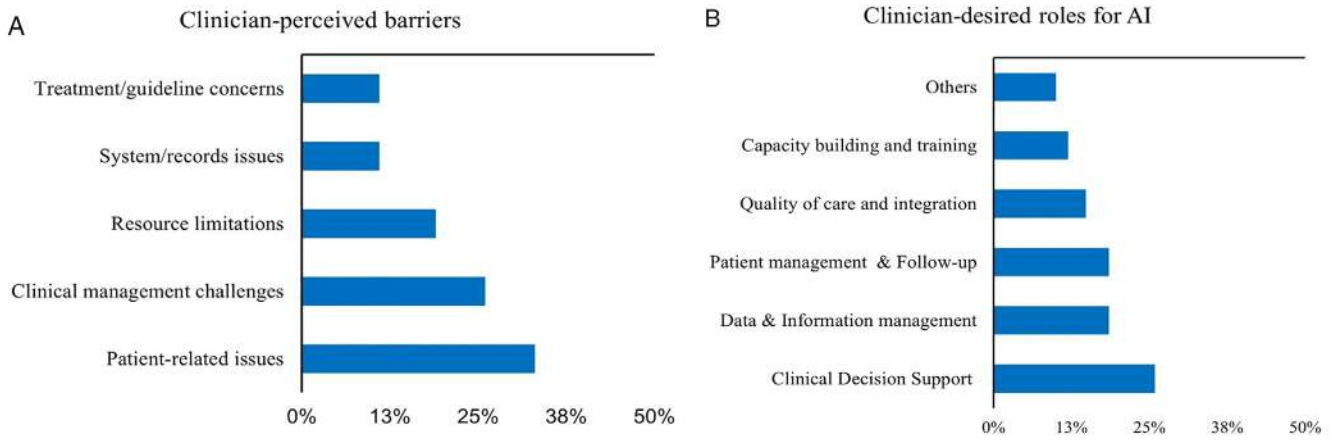

Figure 2. Clinician-perceived barriers to non-communicable disease (NCD) care and desired roles for artificial intelligence in NCD management (n = 29). The figure summarizes survey responses highlighting key challenges in current NCD care delivery (Figure 2**A**) and the areas in which clinicians believe AI could offer the greatest support (Figure 2**B**).

Qualitative usability feedback

The qualitative interviews provided important contextual insights into the real-world use of the NCDAI platform. Two dominant themes emerged: facilitators of use, largely driven by usability and increased confidence, and barriers, primarily related to workflow integration.

Facilitators: usability and increased confidence

Clinicians consistently reported that the platform was easy to use and supported their clinical decision-making. Several described the tool as reinforcing their treatment plans and serving as a convenient point of reference when recalling guideline-based recommendations.

> *"During the training I was able to grasp knowledge of using the app, it's easy. It's not difficult."* – (HCW, Mary Help)

> "' *I've used it for referring to some of the conditions that are out of mind, so it has brought a positive impact to the patient management.*" [HCW_Thika Level 5]

This usability translated into increased confidence and self-perceived guideline adherence, a key component of on-the-job training.

> *"...at the end of the day I'm assured I did the right thing... with the help of the tool, I can say at least I did as the tool suggested."* – (HCW, Makongeni)

> *"...not all of us are up to date with guidelines... having the guidelines incorporated in that platform really helps in decision making."* – (HCW, Karuri L5)

There was evidence of AI-driven clinical decision support in the validation of care pathways employed in the management of clients with non-communicable diseases as opined in the following narration;

> "*I can say it's very assistive. You can give this medication. Sometimes it gives affirmation that the plan that you're using is the same as the one suggested by AI.*" [HCW_Makongeni HC]

Some key facilitators to NCD management included providers perceiving the AI-CDSS as wholistic, encompassing the key components of NCDs. It also facilitated patient-centred education by the health providers. There was mention of NCD services being free and covered under the social health authority's public health insurance scheme in government facilities ensuring accessibility of services.

> "T*he key facilitators is that it is touching most of the contributing factors to NCDs and the complications. So it enables you to memorize, and ask the patient questions concerning all those things. As you educate the patient.*"[HCW_Munyu HC2]

> "*One thing you have is for the government that is free. So the patient usually come here because they would get the drugs for free*. [HCW_Munyu HC2]

Barriers: Workflow integration and workload

Despite high usability and acceptance, a dominant, critical barrier emerged. The tool was not integrated with the facilities' existing paper-based record systems. This created a problem of "duplicative" data entry, which was untenable in a high-workload environment.

> *"The only challenge is really the workload. You're not able to enter the patient's data because it's quite a lot to keep on keying in."* – (HCW, Thika Level 5)

This lack of integration was identified as the single greatest threat to the tool's scalability.

> *"...right now, I must fill manually and then I must go again and fill... It's it's more duplicative for now."* – (HCW, Karuri Level 4)

Discussion

This mixed-methods implementation study provides critical, real-world evidence on the adoption of a generative AI-CDSS for NCD care in Kenya. We have two principal findings. First, the AI-CDSS is technically feasible and demonstrates high clinical acceptance from expert physicians (>93\%) and strong digital readiness from frontline clinicians (86% IT proficient). Second, the primary, and decisive, obstacle to its sustained use is not technological resistance or low usability but severe operational friction caused by its lack of integration with existing paper-based workflows.

Our baseline patient data (N=1929) confirms the profound NCD burden in Kiambu, with high rates of hypertension (72.8%) and diabetes (43.1%). This establishes the urgent need for scalable tools that can support clinicians, a finding consistent with national reports[6,20]. The high expert acceptance rate (93.3%) signals that the NCDAI platform is a clinically valid tool that can help meet this need, aligning with the potential for CDSS described in other studies[17].

The finding that disagreements were concentrated in medication planning is not a failure but a crucial insight for implementation. Managing NCDs often involves polypharmacy and complex decision-making based on comorbidities[7], local formulary availability, and cost[8]. This is precisely the area where an AI's recommendations require the most stringent human-in-the-loop validation. It pinpoints exactly where the AI model needs refinement and where the "expert review" function provides the most value.

Our KAP survey and interview data challenge a common assumption that frontline clinicians in LMICs may be resistant to or unprepared for advanced digital tools. With 69% AI awareness and high IT proficiency, clinicians were not intimidated by the technology. Instead, they embraced it as a tool for confidence and guideline adherence. Their desire for AI to help with "Clinical Decision Support" (26%) and "Data Management" (37% combined) shows they accurately perceive AI's core value proposition.

The qualitative findings on barriers, however, are sobering. Clinicians' complaints about "duplicative" entry and "workload" highlight a classic implementation failure. A tool intended to save time and cognitive load becomes a burden if it adds a parallel, redundant task to an already strained system. This finding powerfully reinforces the core message of health systems strengthening, that high-quality care requires systems designed to support providers, not burden them[12]. The success of AI in this context is less about the sophistication of the algorithm and more about the simple, practical integration with the clinician's existing workflow.

Implications for practice and policy

Our findings suggest three clear levers for scaling AI in Kenyan health systems. First, digitise the foundation. AI tools will not be sustainable as stand-alone applications. Ministries and implementers must prioritise the digitisation of paper-based registers and ensure all new tools are deeply interoperable with the national Health Management Information System (HMIS). This is the only way to solve the "duplicate entry" problem.

Second, use feedback to refine the tool. The expert disagreement on medication plans is actionable data. This feedback must be used to tighten the AI's medication logic, improve its awareness of local formularies, and add guardrails for dosing and contraindications.

Third, build a continuous learning loop. The expert validation module should not just be a one-time test. It should be a permanent feature, creating a rapid feedback cycle where expert comments are used for continuous AI model refinement and to generate micro-learning opportunities for all clinicians using the system.

Strengths and limitations

This study has several strengths. Its mixed-methods design provides a holistic view, triangulating a large baseline patient cohort (N=1929), rigorous expert review (n=300), and in-depth clinician perspectives (n=29 survey, n=11 KIIs). The study was conducted in 10 real-world clinical settings, enhancing the generalisability of its implementation findings.

However, the study also has limitations. The clinician cohort (n=29) was modest and drawn from a single county, which may limit the generalizability of the KAP survey findings. The expert validation used single-expert reviews for each case, precluding an analysis of inter-rater reliability. Finally, as a feasibility and acceptance study, this design was not intended to, and does not, measure the impact of the AI-CDSS on patient-level clinical outcomes such as blood pressure or HbA1c control.

Future work

Future research should advance from feasibility to impact. A pragmatic cluster-randomised trial would be the logical next step to measure the effect of the NCDAI platform on clinical process metrics and patient outcomes. Such a trial must be preceded by the deep integration of the platform into the existing facility HMIS to remove the workflow barriers identified here. Further validation studies should also incorporate multiple expert reviewers to formally assess inter-rater reliability.

Conclusion

This mixed-methods evaluation demonstrates that an AI-driven CDSS for NCD management is both feasible and highly

accepted by expert physicians and frontline clinicians in Kenya. The workforce is digitally ready and perceives clear value in AI support. The primary barrier to implementation and scale is not technological, but operational. The added workload of duplicate data entry into paper-based systems creates an unsustainable workflow friction. To unlock the transformative potential of AI for improving hypertension and diabetes care in Africa, technological innovation must be deployed in lockstep with foundational investments in digitisation and systems interoperability.

Mandatory statements

Ethics and consent

This study was approved by the Mount Kenya University Institutional Scientific and Ethics Review Committee (MKU ISERC, ref: MKU/ISERC/2934). A research license was granted by the National Commission for Science, Technology and Innovation (NACOSTI, ref: NACOSTI/P/24/38726). All clinicians provided written informed consent for participation in surveys and interviews. A waiver of individual patient consent for the retrospective chart review was granted by the ISERC, as all data were fully de-identified prior to abstraction and analysis.

Study status

Data collection and primary analysis for all three components of this study are complete. This manuscript represents the primary findings from the implementation evaluation phase. The NCDAI platform continues to be refined based on these findings.

Data availability

This project contains the datasets generated during the development and evaluation of the NCDAI clinical decision support system for noncommunicable disease (NCD) management across primary health facilities in Kenya. All de-identified datasets used in the study will be made publicly available in a Figshare repository at: https://doi.org/10.6084/m9.figshare.30850829.v3[21]

The repository comprises the following datasets:

- Baseline patient cohort dataset: De-identified demographic, medical history, and clinical parameters collected from participating facilities. This dataset provides the underlying patient characteristics used for evaluating the NCDAI platform's performance and clinical recommendations.
- Expert review and concordance dataset: Contains expert physician ratings and qualitative comments on the NCDAI-generated recommendations. This dataset supports the evaluation of clinical appropriateness, guideline adherence, and inter-expert agreement.
- Clinician knowledge, attitudes, and practices (KAP) survey response data: Anonymised survey responses from healthcare workers assessing usability, acceptability, workflow integration, and perceptions of the NCDAI system. This dataset supports secondary outcome analyses related to feasibility and user experience.

Extended data

Supporting tables, figures and qualitative findings accompanying this manuscript are available as Supplementary materials and can be accessed at: Figshare repository at: https://doi.org/10.6084/m9.figshare.30850829.v3[21]

The extended data include:

Supplementary tables and figures presenting facility-level characteristics, expert feedback categorisations, and clinician-perceived barriers to NCD care.

Detailed examples of expert-reviewed cases comparing NCDAI platform outputs, cited national guidelines, and final adjudicated ratings.

Software availability

NCDAI app

Source code available from: https://github.com/gidyon/ncd-app. The source code, which includes system architecture, implementation details, and technical specifications, is not publicly available. Access can be provided by the corresponding author upon reasonable written request, subject to intellectual property restrictions.

Archived software available from: https://play.google.com/store/apps/details?id=com.aifya.ncd_ai&hl=en

License: Proprietary (under review; not released under an OSI-approved open-source license)

Master prompt

Source code available from: https://github.com/protuso26-max/ncdai-master-prompt.git

Archived software available from: https://doi.org/10.6084/m9.figshare.30850829.v3

License: CC BY 4.0

Acknowledgements

We extend our sincere gratitude to the Kiambu County Ministry of Health, the facility managers, and all the healthcare workers across the 10 participating sites for their invaluable time, collaboration, and insights. We also thank the expert physicians who participated in the validation exercise and the patients whose de-identified data formed the basis of this research.

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Open Peer Review

Current Peer Review Status: ?

Version 1

Reviewer Report 28 February 2026

https://doi.org/10.21956/openresafrica.17542.r33754

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The manuscript addresses an important and timely topic: the feasibility and implementation of an AI-enabled Clinical Decision Support System (CDSS) for non-communicable disease (NCD) management in primary care facilities. The subject is highly relevant, particularly in low- and middle-income settings where digital health innovations are increasingly being explored to strengthen service delivery at a national level. The study has practical value and the mixed-methods approach is appropriate for assessing feasibility and clinician acceptance.

However, several areas still require strengthening before the article can be considered scientifically robust.
First, while the objectives are clearly stated, key constructs such as “feasibility,” “acceptance,” “workflow integration,” and “follow-up time reduction” are not operationally defined with sufficient precision. For example, the reported “30% reduction in follow-up time” is not clearly explained in terms of measurement method, baseline comparator, timing protocol, or statistical testing. It is unclear whether this metric is objectively measured or self-reported by clinicians. These ambiguities must be addressed to avoid over-interpretation.

Second, methodological reporting lacks sufficient detail to enable replication. The sampling strategy for facility records and clinician participants is not described in depth. Inclusion and exclusion criteria for the 200 records reviewed are not clearly specified. In the diagnostic concordance exercise (48/57 cases), the manuscript does not adequately define the reference standard used to determine concordance. Clarification is therefore, needed on whether this was guideline-based, expert-panel validated, or compared against routine clinician judgement.

Third, statistical analysis is limited. The results are presented largely as percentages without measures of uncertainty (e.g., confidence intervals), formal hypothesis testing, or explanation of analytic methods. If inferential claims are being made, appropriate statistical analysis should be described. If the study is purely descriptive, this should be explicitly stated and conclusions moderated accordingly.

Fourth, while ethics approval is reported, the manuscript should provide more detailed information regarding data protection procedures, particularly concerning patient record review and AI system data governance. Clarification on how identifiable data were handled and whether the AI tool stored or transmitted patient-level information would improve transparency in reporting.

Fifth, the conclusions currently extend beyond what the presented data fully support. The findings demonstrate feasibility and clinician acceptance; however, claims regarding efficiency gains and system-level impact should be tempered unless supported by controlled comparative analysis. The limitations section should more explicitly acknowledge potential self-report bias, limited sample size for concordance testing, and absence of a controlled comparator.
To make the article scientifically sound, the authors must:
(i). Clearly operationalize and define all primary outcome measures.
(ii). Provide detailed methodological descriptions to allow replication.
(iii). Strengthen statistical reporting and clarify whether analyses are descriptive or inferential.
(iv). Expand the limitations section.
(v). Clarify data availability and AI governance procedures.
With the incorporation of these revisions, the manuscript has the potential to make a meaningful contribution to implementation research in digital health.

Is the work clearly and accurately presented and does it cite the current literature?
Partly

Is the study design appropriate and is the work technically sound?
Partly

Are sufficient details of methods and analysis provided to allow replication by others?
Partly

If applicable, is the statistical analysis and its interpretation appropriate?
Partly

Are all the source data underlying the results available to ensure full reproducibility?
Partly

Are the conclusions drawn adequately supported by the results?
No

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Clinical decision support systems; Digital health implementation; Health informatics; Non-communicable disease management; Mixed-methods research; Primary healthcare systems strengthening

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have

significant reservations, as outlined above.