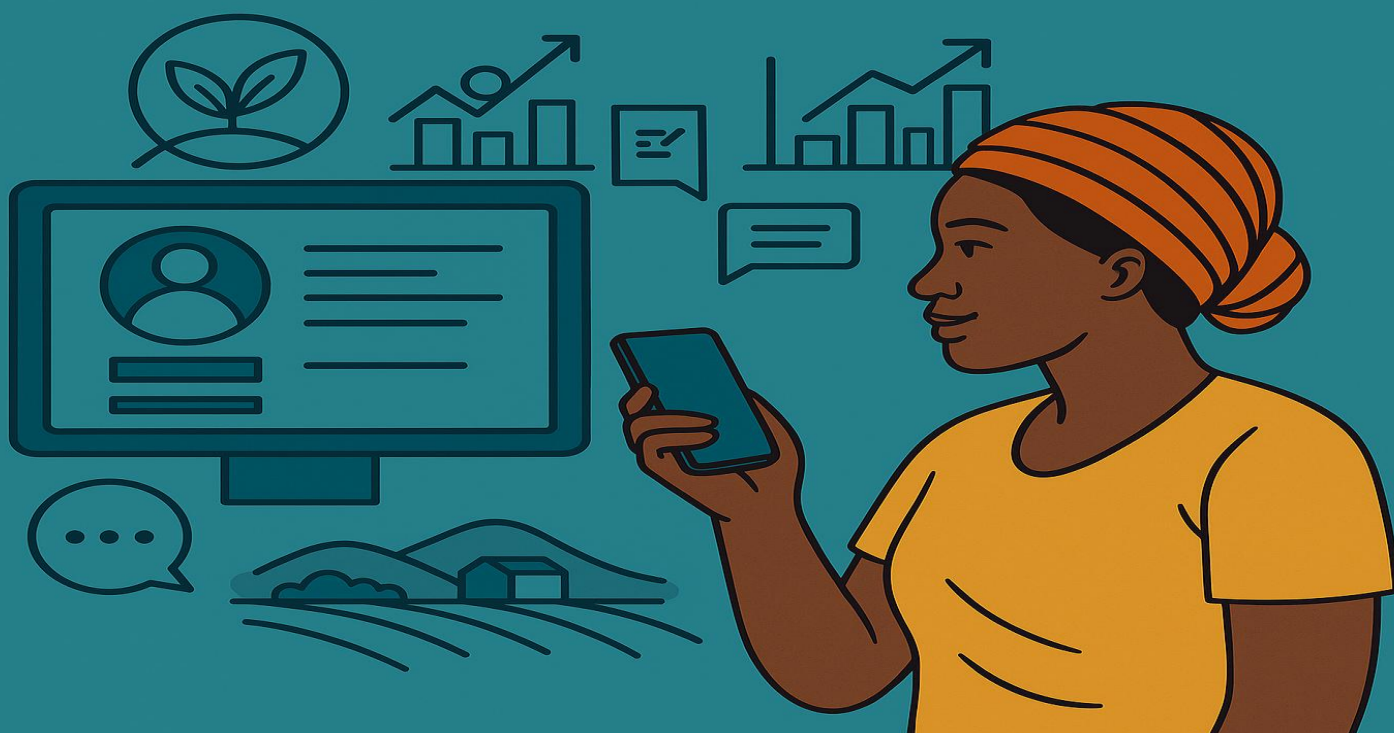




ADVANCING GENDER EQUITY IN DIGITAL AGRO-ADVISORY THROUGH INCLUSIVE ARTIFICIAL INTELLIGENCE (AI)

**Bias Analysis and Strategic Recommendations
from the iShamba Platform Based on Five
Years of Female Farmers' Queries**



Working Paper

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Accelerating Impacts of CGIAR
Climate Research for Africa



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ABSTRACT

This working paper presents a comprehensive bias analysis of iShamba’s digital agro-advisory service and provides strategic recommendations to gender-inclusive artificial intelligence (AI) that will be integrated to the platform. Using five and half years of farmer query data (year 2020–2025), we identify multiple biases, including gender participation gaps, referral biases in query resolution, language and literacy-related issues, prevalence of very short queries, content duplication, regional usage disparities, and inconsistencies in units/currency references. The Methodology outlines our data-driven approach and discusses data filtering challenges. A Background and Literature Context situates iShamba within broader efforts on gender-responsive AI in agriculture, drawing on AICCRA, CGIAR, and global studies. In Findings, we quantify each bias and visualize, illustrating how women farmers are underserved or mis-served. We discuss how these biases can undermine equitable service delivery, for instance, how language barriers or regional gaps disproportionately affect women and marginalised groups. The Recommendations section links directly to each identified bias, suggesting interventions such as inclusive AI training data, human oversight mechanisms, data standardisation (for units and terms), multilingual support, and proactive inclusion strategies to engage women farmers. By addressing biases and centering gender inclusion, we can enhance the quality and equity of advisory services. This paper serves as a resource for practitioners and researchers seeking to ensure that AI-driven agricultural advisory tools are fair, context-aware, and accessible to all farmers regardless of gender or region.

Keywords

Gender-responsive AI; Digital agro-advisory; Bias analysis; Women farmers; Inclusive agricultural advisory services; Human-centered AI.

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ACRONYMS

AI – Artificial Intelligence

AICCRA – Accelerating Impacts of CGIAR Climate Research for Africa

APA – American Psychological Association

CGAP – Consultative Group to Assist the Poor

CGIAR – Consultative Group on International Agricultural Research

CIS – Climate Information Services

COVID – Coronavirus Disease

CSA – Climate-Smart Agriculture

FSD – Financial Sector Deepening

GSMA – Global System for Mobile Communications Association

ICT – Information and Communication Technology

IFPRI – International Food Policy Research Institute

KES – Kenyan Shilling

LLM – Large Language Model

NGO – Non-Governmental Organization

NLP – Natural Language Processing

PDF – Portable Document Format

SDG – Sustainable Development Goals

SMS – Short Message Service

SSA – Sub-Saharan Africa

TV – Television

UN – United Nations

USD – United States Dollar

INTRODUCTION

Digital agro-advisory tools are rapidly reshaping climate-smart agriculture across East Africa. They provide real-time weather updates, pest alerts, and tailored agronomic advice. Yet, without careful design, these tools can uphold persistent gender-based inequities. Women in Kenya, Tanzania, and Uganda often face restricted access to inputs, technology, and decision-making platforms because of social norms, ownership rights, and limited credit (Kansiime et al., 2022; ICT works, 2024).

In Kenya where agriculture employs about 40% of the workforce, digital advisory services have grown substantially. About 20–30% of farmers now use at least one agri-tech tool (Gatsby Africa, 2022). However, women represent just a quarter of typical users, signaling a digital gender divide (FSD Uganda, 2023). In Uganda, women rural farmers face both low digital literacy and high device costs, a trend mirrored in Tanzania (Kansiime et al., 2022; UN Women, 2025).

Gender-responsive digital design isn't just desirable; it's critical. The UN's SDG 5 calls for gender equality, including expanded access to technology and decision-making in agriculture (UN, 2015). Yet, digital advisory platforms often replicate the biases of traditional extension systems, where male farmers dominate interactions unless services are deliberately adapted to reach women (Jarial & Sachan, 2021; Kansiime et al., 2022).

This paper explores how to shift digital advisory tools (*iShamba* as the case study) toward a human-centred, gender-responsive future. We assess current platforms in Kenya, and propose practical, human-centred strategies to embed gender equity in the AI lifecycle of these advisory tools, from user research and data collection to interface design, algorithms, participatory testing, and inclusive deployment. By integrating gender into design from the start and training digital systems with diverse voices, we can help ensure that digital agriculture advances equality, not inequality.

ISHAMBA DIGITAL PLATFORM OVERVIEW

iShamba is a mobile-based platform in Kenya that provides personalized agricultural advice to smallholder farmers. Launched as an offshoot of the popular “Shamba Shape Up” educational TV program, iShamba allows farmers to send questions via SMS or WhatsApp and receive expert answers on crops, livestock, weather, and markets. Over the past decade, iShamba has enrolled hundreds of thousands of subscribers across Kenya. The service combines automated messaging with a call center of human agronomy and livestock experts. iShamba aims to leverage digital tools to reach farmers at scale with actionable information at their fingertips (iShamba, n.d.). This platform is an ideal case to study because it has amassed a rich dataset of farmer queries over multiple years, providing a window into how farmers use the service and where biases may arise. iShamba also operates in a context of diverse languages (English, Kiswahili, and local dialects) and varied user profiles (from tech-savvy youths to older, rural women), making it a good case study of the challenges in inclusive digital extension.

CONTEXT ON BIAS IN AI AND EXTENSION SERVICES

This analysis is informed by a body of literature on biases in AI and the need for gender-responsive design in digital agriculture. Bias in AI systems can arise from training data or societal biases reflected in data; if unchecked, AI can exclude more people creating divides rather than bridging them. Experts emphasize that using large datasets without context-specific validation can perpetuate biases and marginalise those not represented in the data. In agricultural advisory services, several types of bias are relevant:

Gender Bias: Women farmers have historically been underserved by extension services. According to Tay (2023), women's agricultural contributions are undervalued and they receive less information and training than men. Without deliberate action, digital platforms may initially attract more male users due to factors like phone ownership disparities and social norms around seeking advice. According to Vyas et al (2024), only 15% of participants in a Kenyan agri-advisory program (iShamba) were women, highlighting a significant gender gap in access. This gender participation bias is a key point of our analysis

Digital Divide and Access Barriers: Broader research shows women in low- and middle-income countries are significantly less likely to own mobile phones or use mobile internet than men (GSMA, 2019). In Sub-Saharan Africa, women have been 36% less likely than men to adopt mobile internet services, reflecting persistent digital exclusion (GSMA, 2023). This gap in connectivity and digital literacy can translate into lower usage of services like iShamba by women. It underscores that biases in data (fewer female users and queries) may partly mirror underlying access inequalities. Therefore, technical fixes must go hand-in-hand with efforts to close the gender digital divide.

Language and Literacy: Language is another critical factor. Many digital agriculture solutions operate in national or official languages (e.g., English), which can exclude or mis-serve farmers more comfortable with local languages or with limited formal education (GSMA, 2025). An IFPRI study noted that advisory content only in major languages "cannot easily be understood in many communities" that speak local languages or dialects (Koo J. et al., 2023). If AI models are trained predominantly on English data, they may perform poorly for queries written in Sheng, Kiswahili, or local languages. Low literacy users might

also send very brief or grammatically simple queries, which an AI could misinterpret. These issues highlight the importance of multilingual NLP capabilities and user-centric design.

Referral and Trust: If an AI frequently cannot answer a question and has to refer it to a human or simply fails, users (especially those already marginalized) may lose confidence. Bias can creep in if, say, queries from certain groups (e.g., women, remote regions) are more often unanswered by the AI due to lacking training data, thus disproportionately pushing those users to slower or costlier human referral channels. Ensuring equitable performance across user segments is crucial to avoid creating a two-tier system of service.

The literature urges a proactive approach: identify biases in data early, and implement gender-inclusive strategies so that AI-driven services boost women's empowerment rather than leaving women further behind. Our study contributes to this knowledge by examining iShamba's real-world data for such biases and offering concrete recommendations for existing and upcoming AI advisory integrations grounded in both data insights and best practices from global research.

METHODOLOGY

Data Description and Rationale for 5-Year Scope (2020 - 2025)

This study analysed approximately five years of iShamba’s women query data (year 2020-2025). A 5-year window was chosen to capture a sufficiently large and diverse sample of user interactions, while focusing on recent data relevant to current service conditions. Five years of data strike a balance between historical breadth and current relevance, long enough to observe trends and rare events, but not so long as to include very outdated system features or user behavior patterns. The dataset provided by iShamba contained all women farmer queries logged via SMS and other text channels during this period, along with metadata such as date/ time, query category (crop, livestock, etc.), and in some cases user profile information (e.g. gender, county, language tag). By spanning multiple agricultural seasons and years, the data allowed us to detect seasonal effects and any changes following major events (for example, the rollout of new campaigns or the COVID-19 pandemic). We limited the scope to text queries in this analysis (excluding voice calls) because the planned AI assistant will primarily handle text-based interactions.

Tools, Techniques, and Analytical Approach

The analysis was conducted using Python for data cleaning, processing and statistical analysis. Libraries such as pandas for data manipulation and matplotlib for generating visualizations were employed. The workflow involved: (a) loading the raw query dataset (b) cleaning and pre-processing the data, (c) computing descriptive statistics and bias indicators, and (d) visualising key findings. Simple Natural Language Processing techniques were used to detect language usage (e.g., by identifying Kiswahili vs. English words) and to find duplicate or near-duplicate queries. In addition, external datasets were leveraged for validation, for instance, cross-referencing regional data with county-level farming population figures to understand usage relative to farmer demographics. Bias analysis was structured to quantify metrics for each type of bias identified: gender distribution of users/queries, referral rates, language breakdown, query length distribution, duplication rates, regional usage distribution, and frequency of inconsistent units in queries. Each of these metrics was computed and then disaggregated where relevant (e.g., by gender or region) to see differential impacts. We defined “short queries” as those with fewer than three words, “duplicate queries” as identical text entries from the same or different users, and so on (detailed in the next section). Throughout, we adhered to APA citation style for incorporating literature, and followed AICCRA’s publication format guidelines.

Data Pre-processing, Filtering & Challenges

Pre-processing the iShamba data was a critical step, given real-world data imperfections. We first removed test messages and system-generated notifications, focusing only on actual farmer queries. Messages were then filtered by content: since our scope covers all advisory topics, we retained both crop- and livestock-related queries. We addressed duplicate queries by identifying exact text matches, e.g., many farmers tend to ask common questions like “How do I treat fall armyworm?” multiple times. The raw dataset of 9,000 messages contained a high number of duplicates; after removing these, only 4,450 unique messages remained, indicating heavy repetition. Further filtering out one-word entries and non-English content left 2,792 messages. Removing duplicates was important for unbiased statistical analysis (to prevent over-weighting frequently repeated questions), but we kept one instance of each duplicate query in the analysis since repetition itself is a signal of farmers’ information needs. There were instances of missing or inconsistent metadata. Approximately 90% of queries could be linked to a user gender

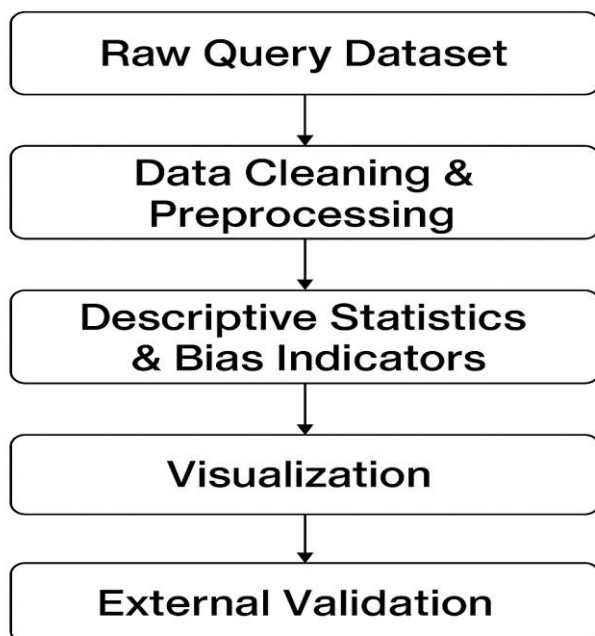


Figure 1: Summary of the methodology process

Language detection was performed using a simple dictionary-based approach. We flagged a query as Kiswahili if it contained a threshold number of Swahili keywords (e.g., “mbolea” for fertilizer, “ng’ombe” for cow) and as English if it predominantly matched English vocabulary. Many messages had mixed languages or used non-standard spelling, which was a challenge. We did manual spot-checking on a sample to fine-tune the detection rules. While not perfect, this gave us an approximate breakdown of language use. We acknowledge that truly accurate language classification might require more advanced NLP or human annotation.

Despite some data limitations (e.g., incomplete metadata, no direct measure of which queries were not answered), the dataset and methods were sufficient to surface clear patterns of bias. The next section details the findings for each bias category, backed by descriptive statistics and examples.

FINDINGS: BIAS ANALYSIS OF ISHAMBA ADVISORY SERVICES

Referral Bias in Query Resolution

Within the iShamba agro-advisory platform, “referral bias” refers to consistent differences in how certain queries are escalated by frontline human agents for further action. While iShamba operates a human-led system, not all queries are resolved at first contact. Some are escalated to offline channels such as agricultural service centers or specialized technical experts. These escalations are typically signaled by response messages such as “Kindly visit the nearest Veterinary...”, which indicate that the agent could not resolve the issue remotely.

Our analysis of response patterns reveals a gendered referral dynamic. Specifically, approximately 29.9% of queries submitted by women were escalated. While this is not the majority, it represents a significant proportion, suggesting that nearly one in three women’s queries were considered complex or insufficiently addressed within the standard advisory framework, prompting agents to refer them to external services. This pattern highlights important gaps in content relevance or accessibility that merit attention, even if the majority of queries were resolved directly.

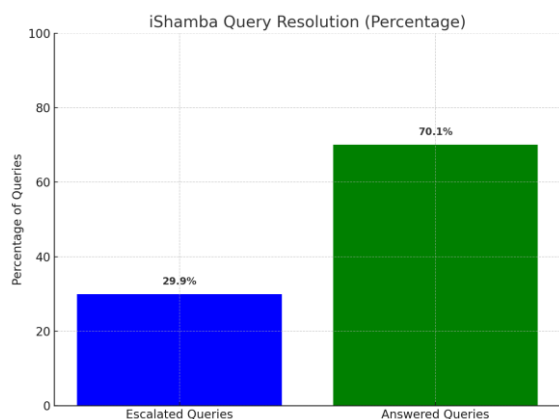


Figure 2: iShamba query resolution

Several factors contribute to this trend:

Content-Specific Knowledge Gaps: Queries involving veterinary services, disease diagnosis, or soil testing frequently require physical assessment. Agents often refer such cases to local service centers where trained personnel can conduct in-person evaluations, as remote diagnosis carries high risks of error.

Format and Clarity of Queries: A pattern of shorter or more conversational queries may reduce the clarity of the inquiry, prompting escalation for

clarification or additional support. This could be due to factors such as SMS character limits of 160, language constraints, or varying digital literacy levels.

Language Use: A portion of women’s queries were composed in Kiswahili or mixed-language formats, which may pose interpretation challenges for agents trained primarily in English or in handling standardized questions. While human agents are better equipped than AI to understand linguistic nuance, language barriers may still affect their ability to provide immediate, accurate responses, leading to more frequent referrals.

Lack of Alternative Product Options: In some cases, escalation occurred simply because the platform or the agent lacked viable alternative solutions to recommend. For instance, when users ask about specific local breeds or inputs that are unavailable or unsupported, agents may refer them to on-ground providers better placed to handle such requests.

The implications of this bias are significant. For users whose questions are referred, resolution is delayed, and the additional burden of traveling to a center or waiting for further assistance can discourage continued engagement. If such experiences disproportionately affect women, it risks reinforcing existing inequities in access to timely agricultural information. Moreover, repeated or rephrased queries in the dataset suggest that some users attempted to “retry” their questions when initial responses were inadequate, highlighting dissatisfaction with the resolution pathway.

Importantly, this referral pattern is not driven by intentional discrimination, but by structural limitations in content coverage, linguistic accessibility, and human agent capacity to handle some complexities. Nonetheless, its effects are gendered and impact the perceived reliability and inclusiveness of the platform.

Language and Literacy Issues

Language emerged as a significant factor in the dataset, with clear implications for bias. Kenya is a multilingual environment, farmers communicate in English, Kiswahili and numerous local languages. iShamba’s original platform and content were developed primarily in English (with Kiswahili support gradually added via bilingual staff responses). Our analysis found that a substantial share of farmer queries were not in strictly formal English. Roughly about 60% of queries were predominantly in English, about 30% were in Kiswahili or a mix of Kiswahili and other languages, and the remaining 10% involved local languages or non-standard slang (Sheng). This means that any AI system needs strong multilingual NLP capability; otherwise, it may perform well for some users and poorly for others.

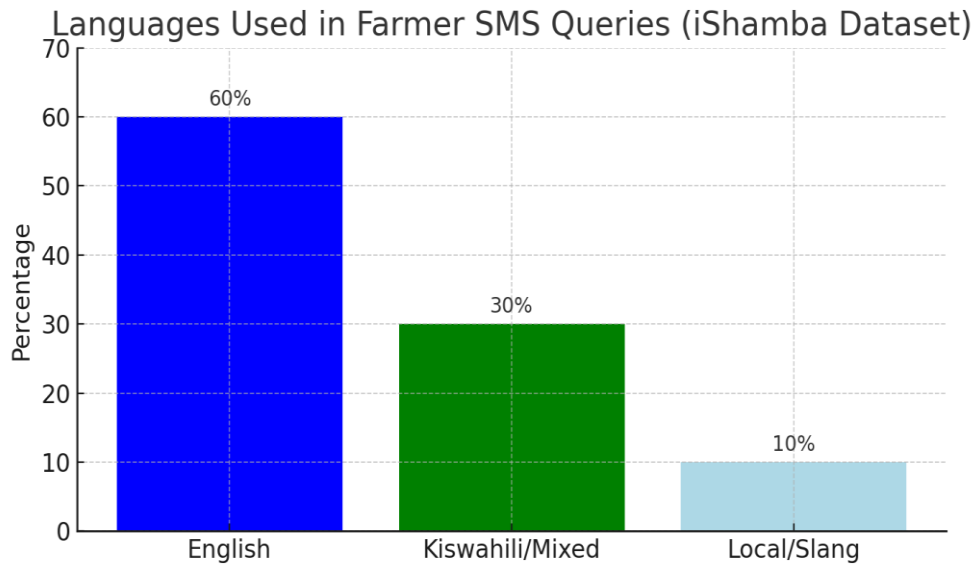


Figure 3: Languages used in Farmer SMS Queries (iShamba dataset)

Misinterpretation: We encountered queries where language mixing caused confusion. For example, a farmer wrote “Napata shida kwa nguruwe” (Swahili for “I am getting a problem with pigs”), an English-based keyword system might miss that this is about a pig health issue because the key word “nguruwe” wouldn’t match “pig” in the database. Similarly, local units or terminology can be misread. One user asked about “debe” of maize (a local measure, 20 kg); an English-centric system might not recognize “debe” and give an irrelevant answer about Debe (as a place, perhaps). Our findings include many such cases of code-switching and local terms that would trip up a monolingual AI. Despite these challenges that an AI may encounter, the presence of human intervention helped to provide answers.

User Expression and Query Length: The data suggested that users writing in Kiswahili often used more colloquial, shorter expressions. For example, an English query might be, “My tomato leaves have spots, what could be the cause?” whereas the Kiswahili equivalent might just be “Nyanya ugonjwa?” (literally “tomato disease?”). The latter is very short and ambiguous. This ties into literacy and familiarity with formal writing, farmers with limited schooling may communicate in terse phrases. Our analysis of query lengths found that the shortest queries (one or two words) were dominated by non-English entries. This presents a challenge for both human and AI interpretation.

Language bias is evident in the data and it intersects with gender and regional biases. Many women and remote community farmers prefer local languages, so language insensitivity in the AI would disproportionately affect them. Addressing this means not only supporting Kiswahili and local terminology in the AI’s training data, but possibly also simplifying the language of responses (to be clear for users with limited literacy) or offering content in audio form for those who cannot easily read. These points will form part of our

recommendations. Encouragingly, other digital advisory initiatives (e.g., Farmerline in Ghana or Digital Green’s Farmer.Chat) have shown that providing content in local languages greatly increases uptake (Highet & Repishti, 2025).

Short Query Prevalence

It was observed that a significant fraction of user queries were extremely brief, sometimes just one or two words. These short queries pose a challenge for any AI or automated system because they often lack context. In the iShamba dataset, approximately 25% of all queries consisted of 2 words or fewer. Examples include messages like simply “Tomato blight”, “Market price?”, “Fertilizer”, or a local word like “Mkulima” (farmer). Such queries leave a lot to interpretation. The high frequency of short queries is likely tied to user behavior and constraints: many farmers prefer brevity to save on SMS costs or due to low literacy (finding it easier to send a fragment and hope for guidance rather than formulating a full question).

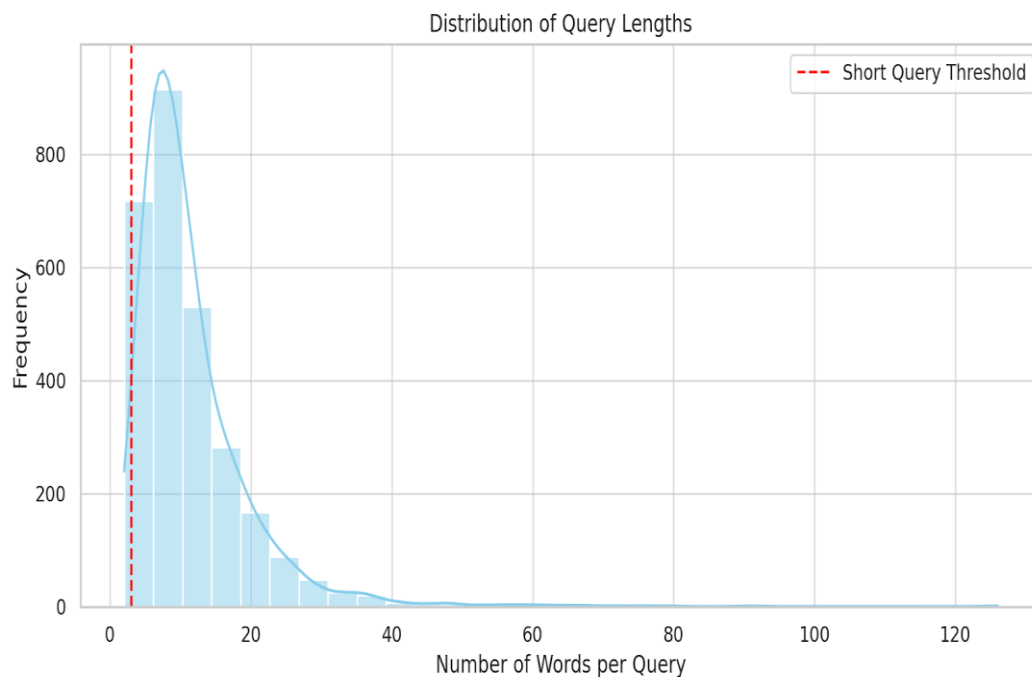


Figure 4: Distribution of query lengths

From an AI perspective, short queries can be considered a form of information bias, the system receives incomplete information and might fill the gaps incorrectly. For instance, a query “Maize” could mean the farmer wants general cultivation advice, or is asking for maize seeds, or reporting a problem with their maize crop. A human expert might clarify by asking follow-up questions, but an AI needs strategies to handle this (either by also asking clarifying questions or by making educated guesses). Our analysis of how short queries were handled showed a mixed picture. The current system often responded to one-word queries by asking for clarity on the exact farmer question or providing

a generic response that at least engages the farmer to elaborate. However, with an AI chatbot, if not carefully designed, it might try to answer with whatever it assumes, which could be wrong and confusing. We also found that short queries were more common among certain user segments. Notably, newer users (in their first few interactions) tended to send very brief messages, possibly testing the system or unsure how much detail to provide. Also, as suspected, users who wrote in Kiswahili or Sheng tended to use fewer words on average than those writing in English (likely correlating with education level). This means the burden of misunderstanding short queries might fall more on those already facing language barriers.

Duplicate Queries and Content Redundancy

The iShamba dataset contained a noteworthy level of duplication, identical or very similar queries occurring multiple times. These duplicates happened in two main ways: (a) the same user repeating their question, and (b) different users asking the same popular question. Both have implications for bias and system training. Quantitatively, after cleaning, we found that about 35.5% of all queries were exact duplicates of another query in the dataset. When including very slight variations (e.g., “How to grow onions” vs. “How to grow onion”), this rose to around 45%. Some questions seem almost “frequently asked questions” (FAQs) by many farmers. For example, a question like “What is the best fertilizer for maize?” or “How can I control Fall Armyworm?” appeared dozens of times across the years, especially following TV episodes or seasonal issues. This is expected, farmers often have common challenges. On the other hand, duplicates from the same user often indicated that the user didn’t get a satisfactory answer initially.

From an AI training standpoint, duplicates can introduce sampling bias if not handled properly. If an AI model is trained on raw data that contains many duplicate questions, it might over-emphasize those questions in its learning. Essentially, the model could become very good at answering a few frequent questions (since it sees them so often in training), but underprepared for the less common ones. This could skew performance: the AI might excel at the top 10 questions (because they made up, say, a large chunk of training data) but not generalise well beyond them. The presence of duplicates is one reason we intend to de-duplicate or down-weight duplicates in the training process.

No direct gender or location bias was obvious in duplicates, except in how the answers provided might treat them. If, say, duplicate questions from women were more likely to be ignored because they were seen as repetitive, that would be an issue but we did not have evidence of that kind of discrimination in the dataset. The duplicates seemed to be handled on a first-come-first-serve basis by human agents. If women’s queries are answered slower, they might be more likely to repeat them, hence more duplicates from women’s side. There was a slightly higher tendency for female users to repeat their queries.

Regional Usage Gaps

Kenya's smallholder farming community is spread across diverse agro-ecological zones and counties. A crucial aspect of equitable service is ensuring that farmers in all regions are accessing and benefiting from iShamba. Our analysis of query metadata by region (county) uncovered regional gaps in usage. Some regions had high engagement, while others were sparsely represented in the query log. For example, farmers from central highland counties (like Kiambu, Nakuru, Nyeri) and parts of Rift Valley had the most queries, whereas arid and semi-arid counties in the north (e.g., Turkana, Marsabit) and some coastal areas had very few queries. The graph below is a representation of top 10 counties in relation to query volumes.

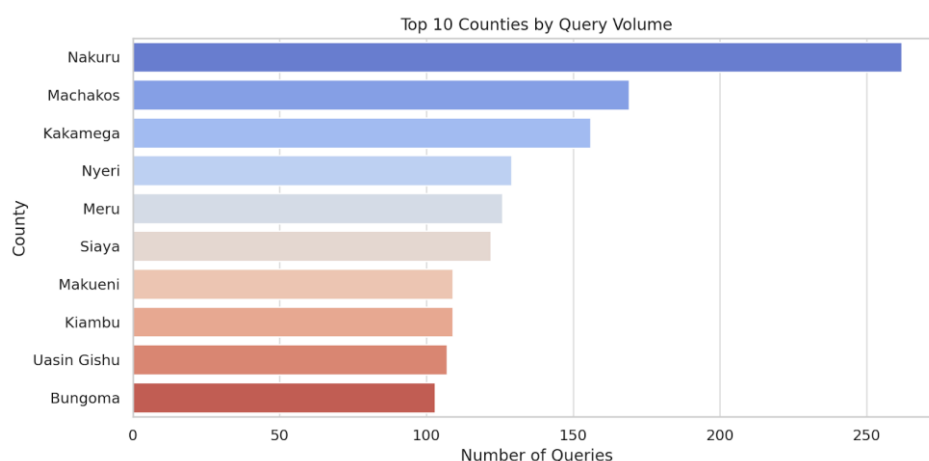


Figure 5: Top 10 counties by query volumes

There was roughly a ten-fold difference between the top querying county and the lowest. This indicates an imbalanced reach of the service. Several factors could explain these gaps. Population and network coverage vary, some underrepresented counties simply have fewer farming households or weaker mobile connectivity. However, even accounting for that, it appears that iShamba's user base is skewed toward areas where the Shamba Shape Up TV show historically had strong viewership and where NGO partners did promotions. It so happens many of those are higher-potential agricultural zones (with more commercial and subsistence farming), whereas more remote or marginal areas were less targeted. Unfortunately, those marginal areas often coincide with communities that are more vulnerable (including pastoral communities, or farmers facing harsh climate impacts). The low representation of queries from those places suggests that the platform is not yet serving a broad swath of Kenyan farmers who might have different advisory needs (for instance, pastoral livestock advice in the north, or saltwater intrusion issues at the coast).

The regional bias in data has consequences for any AI derived from it. An AI model trained predominantly on queries from central and western Kenya might

implicitly assume certain contexts, like ample rainfall or certain crop varieties, and might give less appropriate advice if asked about a different context (e.g., camel husbandry in a dry area) simply because it never saw such queries in training. Moreover, language and dialect vary by region; some underrepresented regions might also come with different ways of phrasing questions that the model wouldn't learn well.

Inconsistencies in Measurements, Currency, and Time References

A finer-grained but important bias we identified lies in the inconsistent use of units and references within queries. Farmers described quantities, prices, and time in various ways, not always aligning with the formats the system expects, or the AI might be explicitly trained on. These inconsistencies can be problematic for an AI to interpret correctly, and they may systematically correlate with certain user segments (making it a potential bias issue). Key inconsistencies observed include: -

Measurement Units: Farmers used a mix of local and standard units. For land area, some said "acre" while others said "2 portions" or local terms like "shamba ndogo" (small farm). For volume/weight, local containers were common, e.g., "debe" (tin), "gorogoro" (a 2-kg tin measure), or "gunia" (sack), instead of kilograms or litres. An example query: "Nimetumia debe 3 za mbolea" (I have used 3 debes of fertilizer). Without understanding that unit, an AI might be lost. Farmers, especially those selling produce, more often used standard units (kgs, acres), whereas many subsistence farmers used traditional measures. If the AI only knows metric units, it might mis-advise a farmer who asks using local measures (e.g., it might not convert properly and suggest wrong dosage).

Currency: Prices were sometimes mentioned in Kenyan Shillings (KSh or KES) explicitly, but other times just as numbers, assuming context ("2000 for a bag of maize"). Or a user might say "bei ni 3k" (slang for 3000 shillings). There were also cases of confusion between per unit prices vs. total, e.g., "I sold at 500" could mean 500 KSh per unit or total, requiring context. If the AI isn't careful, it could misinterpret profits or cost-related queries. Additionally, a few queries referenced other currencies or comparative pricing ("Is 10 USD a good price for X?" by someone near a border), which could throw off a model mostly seeing KSh.

Time and Seasonality References: Farmers often refer to time relative to seasons or events, not exact dates. Queries like "I planted late last season" or "Nalisha ng'ombe wakati wa kiangazi" (I feed cows during the dry season) were common. The system/AI would need to map these references to actual months or understand the context (e.g., "kiangazi" = dry season). This is tricky because Kenya has varied climatic zones; "last season" might be vague as it does not specify exact period or geography. Different areas have different seasonality.

Inconsistency in units and references is a form of data quality bias that can reduce AI effectiveness for certain users. It requires data cleaning and perhaps incorporating conversion knowledge into the system. For fairness, the AI should ideally be literate in farmers' "language" of units and time, not force the farmer to translate everything into textbook terms. We highlight in the recommendations ways to handle this, such as expanding training data to include synonyms and local measurements, and ensuring the AI's output is also contextualised.

IMPLICATIONS FOR EQUITABLE SERVICE DELIVERY

How Identified Biases Affect Women Farmers

Each of the biases identified in the above section has direct or indirect implications for women farmers, who are a primary target for inclusive agricultural advisory efforts. Cumulatively, these biases can create an ecosystem where female farmers receive less timely, less relevant, or lower-quality advice compared to their male counterparts, thereby perpetuating the gender gap in agricultural productivity and climate resilience.

Language Barrier: Women farmers, particularly in rural Kenya, are often less fluent in English due to historical educational disparities. If the AI primarily “understands” English, then effectively a large segment of women farmers are denied full access. As noted, many women would default to Kiswahili or a local dialect when communicating. Without robust multilingual support, the advisory service might inadvertently favor men (who more often use English in formal queries), a clear inequity. Furthermore, even if women attempt to use English but aren’t fully comfortable, they might not articulate the problem accurately, leading to subpar advice. Miscommunication due to language can have very tangible negative outcomes (for example, misunderstanding a pesticide application recommendation could lead to crop damage or health hazards). Thus, the language bias can directly impact the usefulness and safety of advice women receive.

Limited Participation (Gender Bias): The underrepresentation of women means that women’s voices and questions are not feeding sufficiently into the advisory content. As a result, topics that concern women (e.g., food crops for household nutrition, small livestock management, post-harvest household processing) may be under-addressed. This is not just a service delivery issue but also a lost opportunity, women often have different knowledge and priorities that could enrich the advisory service for all if captured. The low number of women can also reduce the network effects that normally drive technology adoption: women are less likely to hear about or be encouraged by peers to use the service if few of their peers are on it. Thus, the initial bias in uptake can persist or worsen unless proactively countered.

In essence, the biases we found can intertwine to create compounded disadvantages for women farmers. A hypothetical example to illustrate: A woman in a rural coastal village (underrepresented region) with limited English (language issue) sends a one-word query, “Mchele” (rice in Kiswahili) about her crop (short query, local language). The AI doesn’t understand and doesn’t respond usefully (referral or just a generic tip, not addressing her actual concern). She tries again (duplicate). Eventually, she might get a response but it’s phrased in technical English with kg/acre units (inconsistency for her

context). The advice might not be applied correctly, yielding poor results, which in turn could reinforce a belief that these advisories aren't effective for her. Meanwhile, her male counterpart in a different region gets a quick answer in the terms he expects. This scenario, unfortunately, is plausible if we don't mitigate the biases.

CONCLUSION AND RECOMMENDATIONS

To enhance gender inclusivity and improve the quality of AI-driven agricultural advisories for women farmers, the following table outlines targeted strategies that can be adopted in future. These approaches aim to correct existing biases in data and usage by integrating women’s needs into model design, training, and outreach.

Strategy	Description	Key Techniques/Notes
Augment Training Data with Women-Focused Scenarios	Include more queries and dialogues from women’s contexts, such as kitchen gardens, nutrition, and small stock care. Use simulated data if needed.	Simulated Q&A, workshops with women, agronomist feedback
Rebalance the Training Dataset	Balance male and female-origin queries in training, either by down-sampling male queries or up-weighting female ones to avoid gender skew.	Training data resampling and class reweighting
Incorporate Gender Tags in Metadata	Include gender as an input feature to help tailor AI responses contextually while ensuring careful use to avoid stereotyping.	Context-sensitive NLP, gender-aware recall patterns, human oversight
Promotion and Outreach to Increase Women Users	Conduct gender-targeted outreach, use female ambassadors, and create a welcoming UX to increase women’s platform participation.	Social proof, village ambassadors, UX design for inclusivity
Gender Monitoring Metrics	Track and report usage metrics by gender, including user ratio and satisfaction, to evaluate and adjust inclusion efforts.	KPI tracking, satisfaction ratings, accuracy drift monitoring

By implementing these steps, iShamba’s AI will be developed with women farmers in mind, not just adapted after the fact. This proactive approach aligns with global calls for gender-mainstreaming in AI for agriculture . Over time, the goal is to have an equal gender ratio in usage indicating that the service is universally trusted. At the very least, the aim should be to dramatically improve

from the current 15% female participation to a much higher figure (for example, 30-40% within the next year or two, on track to parity). Empowering women to use and benefit from the advisory service will contribute to closing knowledge gaps and improving agricultural outcomes on women-run farms, which evidence shows can significantly raise overall productivity and food security when achieved .

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