Disrupting agricultural advisory utilizing generative AI: Lessons learned from Minimum Viable Product development of the Agricultural Information Exchange Platform

AIEP Initiative[*] , Stewart Collis[1], Florence Kinyua[2], Vikram Kumar[2], Howard Lakougna[1], Christian Merz[2], Kirti Pandey[†2], and Christian Resch[3]

[1]Gates Foundation
[2]Deutsche Gesellschaft für International Zusammenarbeit
[3]CLEAR Global

2025

Abstract

Existing agricultural advisory systems fall short in providing real-time, relevant, contextual advice in preferred modalities such as natural conversations in local languages. The Agricultural Information Exchange Platform (AIEP) is a two-year Gates Foundation investment, to pilot AI-driven, gender-sensitive digital advisory services for smallholder farmers in Kenya and Bihar, India. Targeting low-literate and low-digital-skill populations, AIEP convened five multi-stakeholder cohorts to develop Minimum Viable Products (MVPs) that integrate generative AI, multilingual speech technologies, and omni-channel delivery mechanisms. Using agile, collaborative innovation processes, the cohorts built solutions that employ Retrieval-Augmented Generation (RAG), local language processing, and curated agricultural datasets to deliver personalized, context-specific advice via accessible channels such as IVR, Social Media, and mobile apps. Results from over 800 farmer surveys show high user satisfaction (average NPS 60) and potential for meaningful impact, though challenges remain in local language coverage, content completeness, integration with complementary services, and long-term sustainability. The initiative identifies key digital public goods—including data-sharing infrastructure, a common agricultural corpus, language technology, and benchmarking tools—as critical enablers for scaling. AIEP's experience informs the proposed Global Facility for Generative AI-Driven Agricultural Advisory, aiming to coordinate data, models, and open-source tools with country-led implementations, fostering an inclusive, interoperable ecosystem for AI-enabled agricultural extension in low- and middle-income countries.

1 Introduction

The Agricultural Information Exchange Platform (AIEP) is a 2-year 4-million USD grant by the Gates Foundation that aims to enhance advisory information exchange (i.e. agricultural extension) for serving low-literate, low-digitally skilled and women farmer populations in selected rural target geographies, beginning in Kenya & India.

AIEP is integrated with the larger BMZ funded program of "FAIR Forward – Artificial Intelligence for all"[1]. GIZ as the implementing partner in cooperation with Clear Global convenes five cohorts across partner organizations including public, private and NGO service providers to develop five Minimum Viable Products (MVP) utilizing innovative and/or nascent technologies such as Machine Learning personalization and new omni-channel delivery mechanisms including speech recognition and generative AI in local languages.

The MVPs test and evaluate the long-term potential for a scaled, integrated, customized, and cross-sector advisory information exchange platform solution and potential to develop a digital public good platform that can be adapted for a variety of use cases.

Using the AIEP in India (Bihar region) and Kenya as a case study, we showcase how emerging

[*]The AIEP initiative was a collaborative undertaking and this paper summarises inputs and thoughts of many who were involved but especially the members of the cohorts. This is to represent their shared contribution. The remaining authors are the GIZ core team with support from CLEAR Global and the team at the Gates Foundation and are listed alphabetically.

[†]Current affiliation: Independent

[1]See `https://www.bmz-digital.global/en/overview-of-initiatives/fair-forward/`

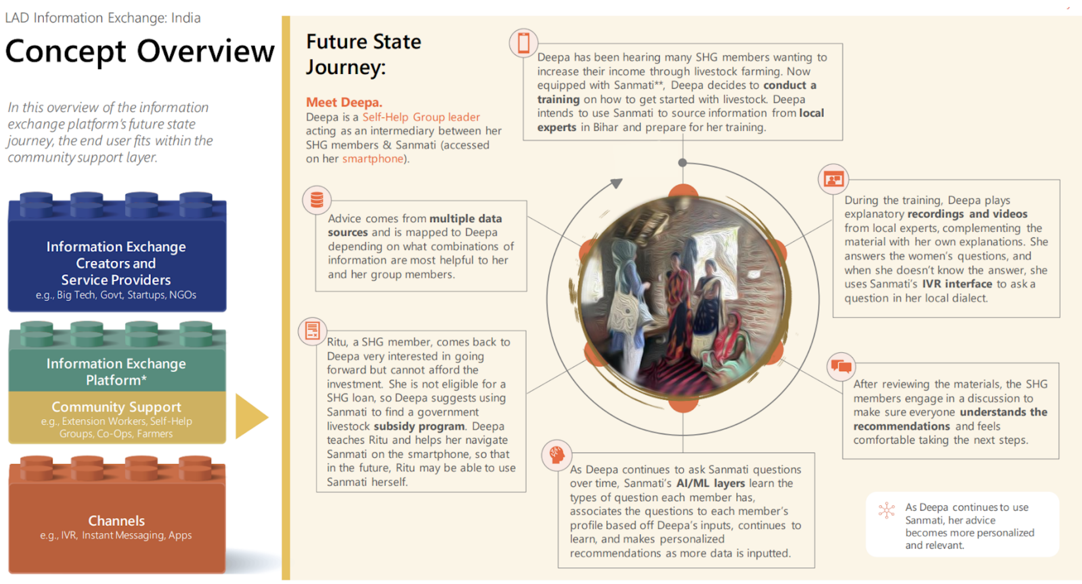


Figure 1: Future state end user journeys, in this case for India

technologies and particularly AI enhance inclusive digital agricultural advisory.

The AIEP grant has been launched as part of the Gates Foundation's (GF) "Learning Agenda on Digital", a Gates Foundation internal challenge to explore cross-cutting digital tools, enablers, and platforms that could have broad applicability and thus may be better pursued in a coordinated way across the foundation's programs. Prior to the grant being awarded to GIZ, a rapid exploration, discovery and prioritization study was executed with some ground truthing to deepen the cross-country understanding of the advisory needs of farmers in Kenya and Bihar, India. This exercise entailed interviews with 61 potential end users and 37 experts. To suit the needs of different archetypes of end users including individual farmers, farmers in cooperatives, farmers in self-help-groups as well as extension workers several design principles, future state end-user journeys and basic system architecture for the AIEP has been developed, see Figures 1 and 2.

This paper focuses on the innovation methodology and explores the solution space of generative AI based advisory services for smallholder farming systems and shares experiences and lessons learned from the MVP development of AIEP between February 2023 and April 2025. Apart from this document there is another paper available that provides a deep dive into the AI technology used for AIEP (see AIEP Initiative et al. [2025]).

2 Problem Statement

Smallholder farmers are vital for global food security, yet they often lack access to localized, timely, and actionable agricultural information, particularly in low- and middle-income countries [Fabregas et al., 2019, Faure et al., 2012, Zerssa et al., 2021]. This information gap hinders productivity, profitability, and the adoption of sustainable practices [Davis et al., 2014, Fan and Rue, 2020]. Although agricultural extension services are designed to address this issue, traditional models relying on extension agents struggle to deliver precise, plot-specific advice at scale due to logistical challenges and the variability of local farming conditions [Ferroni and Zhou, 2012, Msuya et al., 2017, Nedumaran and Ravi, 2019, Raabe, 2008].

Emerging technologies hold an immense potential to transform agricultural advisory. Digital advisory solves the challenges of physical availability, adaptability and cost-efficiency that traditional advisory and public extension systems face [Islam et al., 2017, Sanga et al., 2013, Saravanan, 2010, Spielman et al., 2021, Tata and McNamara, 2018, Kachelriess-Matthess et al., 2018, Silvestri et al., 2021]. However, the design and usability of digital agricultural advisory services are crucial as farmers are often amongst the most vulnerable with low literacy and digital skills and struggle to access digital information and services. Frequently, when farmers cannot access these solutions in their local language, they cannot access digital solutions at all.

Landscape analysis research highlights the gap of current solutions [Gates Foundation, 2024]. Existing advisory and public extension systems fall short in providing contextual, localized and personalized advice in preferred modalities such as natural conversations in local languages. For instance, in Kenya, the extension worker to farmer ratio is 1:1000 making it a challenging task to serve farmers sufficiently [Government of Kenya et al., 2014].

Design Principles	How might we...	Path to Apply Principle
1. Trustworthy	Design the platform so that it builds trust with end users by delivering trustworthy information through trusted individuals and providers?	Ensure that initial interaction with the platform is through a trusted source, including existing service providers and/or intermediation by a person (who, whenever possible, is already part of the local community).
2. Suitable for intermediaries	Help intermediaries deepen their impact with end users by designing the platform to help intermediaries both better serve individuals and scale their work?	Make the platform suitable, helpful, and attractive for local intermediaries to use with the end users they serve, both one-on-one and at scale.
3. Accommodate ranges of digital literacy and access	Accommodate content and interfaces to a range of literacy skills and channels?	Design omni-channel solutions, including voice, that accommodate and build a range of literacy and digital literacy skills.
4. Considerate of language needs	Account for the innumerable dialects and lack of existing resources in languages spoken by low-literate and low-income users in our target geographies?	Leverage existing language platforms and incorporate an inclusive strategy to reach those marginalized through language.
5. Conscious of gender norms and women's needs/access	Design a source of information that is mindful of women's contexts but also provides access despite existing traditional social and cultural gender norms?	Engage female interviewees from both end-user and expert interviews for input throughout exchange development, designing with women in mind.
6. Results oriented and applicable advice	Design a solution that gains end users' trust by showing proven results & outlining clear next steps for application?	Show proven success in stories, videos, and other end-user friendly formats to build credibility.
7. Localized	Combine large-scale sources of information into one platform while still making relevant information feel familiar and personalized to the farmers?	Implement feedback loops and relevant information updates to reflect what users are experiencing locally
8. Focused on financial empowerment	Design in consideration of end users' financial access barriers so that end users can realistically apply advisory information?	Incorporate providers with the ability to share financially empowering services and information.
9. Focused on holistic development KPIs	Track the success of the project on metrics that matter to end users?	Generate end-user context specific holistic development KPIs and track them.

Figure 2: Design Principles for an AI driven agricultural advisory system based on ground truthing studies in Bihar, India and Kenya.

Efforts of digital agricultural advisory to close this gap show first traction: According to a survey with more than 1400 smallholder farmers, 56% of farmers in Kenya use digital farmer services. Yet, usage is often superficial and geographically highly unequal: Only about 27% of registered users are meaningful users with perceived benefits and repetitive usage over a longer period [60 Decibels, 2025]. In contrast to Kenya, the estimated proportion of active users of digital farmer services in Sub Saharan Africa overall is about 5%, hampered by barriers to adoption including digital literacy, language literacy, relevance of information, awareness and cost [Gates Foundation, 2024].

3 Related Work

3.1 Agricultural extension

Traditional agricultural extension services are crucial for sharing knowledge with farmers but face major limitations in low- and middle-income countries due to a shortage of agents and a top-down approach that limits farmer engagement [Msuya et al., 2017]. There is insufficient investment in National Agricultural Research and Extension systems. Most smallholder farmers never interact with an advisor. Many extension systems lack effectiveness with outdated content. Agripreneur models are promising but have yet to find business models to scale and sustain. Peer-learning models like farmer field schools help but are hindered by limited resources and inconsistent outcomes due to diverse farming conditions [Feder et al., 2004, Waddington and White, 2014, Waddington et al., 2014].

To overcome these challenges, ICT-based interventions—such as SMS and voice systems—have emerged, delivering localized, timely information with demonstrated benefits, including increased yields and income [CTA/Dalberg, 2019, Beanstalk AgTech, 2023]. The investments in global Ag-Tech in LMIC has significantly increased in quantity and diversified and most of today's digital agriculture solutions target agricultural advisory[2]. However, they depend on curated content, which restricts flexibility.

3.2 LLMs and language AI overall

Chatbots are increasingly used in agriculture to deliver information through natural language, with projects like Hello Tractor and Avaaj Otalo offering advice via voice or text [Jain et al., 2018, Patel et al., 2010, 2012]. However, traditional rule-based chatbots struggle with complex, evolving queries and lack personalization due to limited adaptability and data integration.

Advances in foundational AI models by major technology companies like LLM's are occurring at a remarkable pace, with potential availability for global use—including AI4D applications—within months. Generative AI can dramatically improve quality of, and accelerate access to, higher quality information and services for smallholder farmers. AI-driven chatbots use machine learning and natural language processing to provide more flexible, personalized, and data-informed responses. They adapt to real-time data and offer higher user satisfaction and better contextual understanding.

Apart from AIEP there is an emerging group of innovators that experiment with Gen AI based advisory services. These solutions overcome barriers to adoption such as digital literacy, language literacy, and relevance; can provide personalized advice

[2]See the Digital Agri Hub by Wageningen University & Research, available at https://digitalagrihub.org/

by gathering more in situ information about farmers; and real-time analytics provide new insights into farmer behavior. For example, iSDA's Virtual Agronomist has been used by over 87,000 farmers as of February 2025 who reported a mean yield increase of a factor between 1.4 and 1.9 compared to farmers not using the service [Shepherd et al., 2025].

In India, Samagra's Ama Krushi has been deployed to almost 10k extension workers in Odisha and Uttar Pradesh, India. One of the larger scale solutions is KissanAI with 120k+ farmers reached and a multimodal LLM specialized for agricultural domains like crop diseases[3]. Smaller scale trials like Opportunity International's Ulangizi AI[4] or C4IR's chatbot in Rwanda are equally promising and actively contributes and exchanges knowledge and know-how with the AIEP cohorts. In terms of international agricultural input providers Bayer, BASF and Syngenta engage on their own and develop early pilots targeting smallholder farming systems. Another early trial called mzee.ai is a recent attempt to combine language AI with gamification by CIAT and the Pan Africa Gaming Group.

Furthermore, initiatives such as Generative AI for Agriculture (GAIA) (reasoning corpus)[5], Masakhane' African Language Hub for AI (local language AI)[6], and Open Agri Net (digital agriculture DPI)[7] align closely with the goals of AIEP. Integration with and monitoring of other investments, such as the UAE-supported Falcon-based agricultural sector-specific large language models[8], is also essential.

4 AIEP's innovation process

Taking decades of experiences in digital farmer services provision and most recent technological advancements in generative AI into account the AIEP project combines two goals in its methodology to develop the MVP's:

1. combining past experiences, research and networks and activities with additional testing and research during the development process, to learn as much as possible from a wide variety of approaches while
2. ensuring the emerging technology assets and digital public goods are created by a community of actors that trust and cooperate with each other.

For this, AIEP applied a methodology that iterates between parallel work on a manageable number of MVPs with phases of consolidation and recombination. In parallel work, the cohorts separately build on their ideas and later MVPs, solving either for the entire AIEP concept or critical parts of it. In phases of consolidation, they come together, synergize on pieces from each other and combine efforts.

The innovation process started with collective ideation and has been based on the assessment of prior research including the GF's digital agriculture roadmaps and LAD research, inputs from key partners, and lessons learned from GIZ's agricultural and digital portfolios in India and Kenya. Ultimately, we build upon refined use cases for end user tested MVPs of the agricultural information exchange platform for market entry. These MVPs are constituted by modules and interfaces that create functional and tested instances of the AIEP.

Accordingly, the innovation process comprises 3 phases, namely an

- Ideation,
- Development and
- Consolidation phase

The 3 phases are also reflected in the logframe of AIEP with outcomes, outputs and success indicators according to each individual phase. However, we also appreciate the fact that the reality of the cohorts as well as the nature and development of their MVPs in an innovative process requires flexibility and adaptation during the implementation of this activity. We therefore included anticipated decision points and adapted the methodology iteratively to serve the needs of the cohorts and the overall goal of this investment.

Apart from the innovation process phases, our approach rests on four pillars:

1. The use of open AI and digital technology in the form of digital public goods (DPG's)[9]
2. The aim to develop markets, ecosystems and structures for easier adoption of open AI and digital technology
3. The involvement of local partners including end users and local tech actors to support them in developing solutions for their communities

[3] See https://kissan.ai/

[4] How AI is Revolutionizing Smallholder Farming in Africa with FarmerAI, available at https://opportunity.org/news/blog/2025/february/how-ai-is-revolutionizing-smallholder-farming (accessed 1st of August 2025)

[5] see project description at https://www.ifpri.org/project/generative-ai-for-agriculture-gaia/

[6] See https://www.masakhane.io/masakhane-ai-hub

[7] See https://openagrinet.global/

[8] See AgriLLM Unveiled at COP29: Transforming Global Food Security with AI, available at https://ai71.ai/news/8/agrillm-unveiled-cop29-transforming-global-food-security-with-ai (accessed 1st of August 2025)

[9] See https://www.digitalpublicgoods.net/standard

4. Principles for the responsible and human-rights-based usage of data and AI (e.g. in the EU Ethics Guidelines for Trustworthy AI[10]), the principles of the FAIR Forward program and the Recommendation on the Ethics of Artificial Intelligence by UNESCO[11]).

4.1 Ideation

The project's ideation phase on the MVP development of the AIEP lasted about 3 months and involved a Call for Proposals (CfP) that was widely distributed and resulted in 133 concept notes. These concepts were assessed on various criteria, leading to the selection of 30 cohorts for the following ideation workshops. The selected cohorts comprised a mix of local and global players intending to work in Bihar, Kenya, or both. Among all partners making up the cohorts, 31 were from India, 21 were from Kenya and 31 were global players.

The ideation workshops pursued the following goals: (1) to establish the final cohorts, (2) to finalize product visions per cohort and (3) to define a 1st iteration of the architecture of the information exchange platform. Moreover, potential bottlenecks of the local ecosystems (e.g. access to target groups, community engagement or data access) were discussed to address them collectively. In addition to the cohorts, individual technical experts as well as farmer and extension officer representatives were invited to these ideation workshops to provide further feedback and initial end user reactions to the cohorts' concepts.

The ideation workshops received positive feedback, with participants appreciating the inputs on women inclusion, end user engagement, and opportunities for exchange. Key learnings from the workshops highlighted the diversity among smallholder farmers and the importance of two-way communication. Trust-building, validation of information, and consideration of local languages and gender dynamics were identified as crucial for the MVPs. Following the ideation workshops, 27 revised proposals were submitted. The final selection out of those proposals was based on revised criteria from the first selection and was undertaken by a Technical Advisory Panel consisting of six external experts alongside teams from GIZ and the Gates Foundation.

The concepts were rated on technological innovation (20%); end user and community orientation (20%); gender-inclusive aspects (20%); impact orientation, evidence, and user feedback (20%); local representation (15%); long term sustainability and clear ownership of the MVP (5%) and a yes/no criteria of the openness of the developed resources to follow the commitment to Digital Public Goods.

Finally, the cohorts selected to develop the MVPs of the AIEP include

- **dynAg, a partnership between IRRI, CIMMYT, Dexian India Technologies Private Ltd., Gramhal, IFFCO Kisan, H3i Technologies Private Limited, MICROX Foundation and Sumarth -** The dynAG cohort focuses on Bihar only and is led by the CGIAR, namely the International Rice and Research Institute (IRRI) and CIMMYT. Dexian oversees application development (system integrator) supported by H3i Technologies (UX and LLM integration). End user engagement and farmer facing field support is covered through IFFCO Kissan and Sumarth utilizing ongoing partnerships for example with JEEVIKA. The dynAg platform is an extended version of the 'matar' application developed by H3i Technologies and is available via the ai.sakhi app and IVR.

- **Farmer.Chat, a partnership between Digital Green, Karya, Gooey.ai, Gramvaani -** The cohort includes Digital Green, one of the leading non-profit organizations in the digital agriculture space along with its partners Karya Inc, Gooey.ai and Gramvaani. Gooey.ai brings a deep expertise in LLM pieces, tools and models including benchmarking and evaluation. The company is working with Karya Inc. for time-efficient fine-tuning and some parts of the ASR pipeline. Graamvani is supporting by developing an IVR pilot for the solution. The MVP development builds upon the generative AI-powered chatbot Farmer.Chat.

- **Tech4Her, a partnership between DeHaat and Dalberg -** The cohort comprises two entities: DeHaat, a well-known agri-tech startup in India with a presence across various geographies, and Dalberg, which has developed a Human-Centered Design (HCD) toolkit for user research. The Minimum Viable Product (MVP) is an open-source architecture enabling customized, inclusive and interactive information exchange by last mile women farmers & extension agents, interoperable with omnichannels interfaces. The cohort leverages on the extensive end-user knowledge of Dalberg and access to internal agricultural data from DeHaat.

- **Viamo, Sahay, HarvestPlus and Producers Direct -** This cohort covers both piloting regions (Kenya and Bihar) and develops

[10] See https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai

[11] ICTforAg 2024 – Localizing Impact, see https://www.ictforag.com/

the MVP on top of Viamo's IVR service. Sahaj contributes their tech expertise and have key roles in supporting the development of the speech technology and Large Language Model (LLM)-based RAG pipelines. HarvestPlus and Producers Direct take over user testing with farmers through their network and contribute agricultural datasets.

Apart from the 4 selected AIEP has onboarded a 5^{t}h cohort for the last 6 sprints of the MVP development process. This cohort comprises **Opportunity International, DigiFarm and Gooey.ai** and has implemented a WhatsApp based bot in Kenya that emerged out of a custom-built solution tested in Malawi with 150 users[12]. Opportunity International is an international NGO who has the role of integrator and subject matter expert on Extension Services and the deployment of AI bot for Ag Extension. DigiFarm, the Kenyan entity and wholly owned subsidiary of Safaricom, has local knowledge in Kenya and sources advisory content. Moreover, DigiFarm has exceptional access to farmer communities and coordinates the field outreach and research. Gooey.ai provides a low-code AI orchestration Platform comprising technical services for the conversational interfaces, hosts RAG tools, function interfaces for external services and the WhatsApp interface, logs and analysis results, orchestrates knowledge, prompts and natural language processing.

This 5$^{\text{th}}$ cohort joined AIEP on its own cost without receiving any funding. Some of the value adds and benefits to onboard an additional cohort includes to strengthen AIEP's engagement in Kenya, technical similarities and shared learnings with the 4 cohorts (e.g. in terms of local language model performance, architecture, user experiences). In addition, the 5$^{\text{th}}$ cohort provided another opportunity on exchanging more data across cohorts, share expertise and knowledge, discuss alternative solution packaging and business models as well as reusable parts and components of their MVP.

Besides differences in channels and languages, the 5 MVPs set themselves apart by (1) the agriculture content used, (2) the LLM used, and (3) the system design of their architecture. All MVPs use large language models such as BERT, LLaMa or GPT to link information requests and feedback to available agricultural data.

After the final selection, the project moved into the MVP development phase. Workstreams for architecture, monitoring and evaluation (M&E), language technology, end user engagement, and Digital Public Goods were initiated, with a focus on architecture and M&E in the early stages of the MVP development.

[12]See https://opportunity.org/news/blog/2025/february/how-ai-is-revolutionizing-smallholder-farming

4.1.1 Development

Building a shared product vision and developing MVPs necessitates a rare blend of technical expertise and multidisciplinary collaboration beyond a core team of software developers. AIEP applied agile methodologies to increment on MVP development, to foster cross-partner cooperation and to share knowledge of common interest. The MVP's have been implemented iteratively in monthly sprints to build the solutions in small, incremental stages. Within the 2-year time frame of the project 17 sprints have been conducted. Each sprint had a clear goal and focused on completing a specific set of tasks from the product backlog and supportive activities e.g. on Monitoring & Evaluation, end user engagement et cetera.

At the end of each development cycle monthly sprint reviews have been scheduled for 2 hours where the teams demonstrated the completed work to the other cohorts and selected stakeholders and gathered feedback. Representatives of each cohort presented the implemented product enhancements including functions and features, end user outreach and field testing, updates on AIEP's standard indicators, engagements in national or regional initiatives etc. In addition, the cohorts reflected on the sprint, identified what went well, what could be improved, and how to improve future sprints. Usually, the participants applied peer reviews between two assigned cohorts to provide feedback also taking experiences and lessons learned from the peer cohort into account. The cohorts presented also on their sprint goals for the upcoming period. Most cohorts run their development progress in 2-week long sprint cycles so that the AIEP-wide sessions happen about every second sprint for the cohorts. The monthly format has been a compromise between frequent updates and keeping a low burden for the cohorts. Each session has been recorded, and recordings are available in shared cloud storage.

Overall, the sprint reviews enhanced the collaboration and communication between the cohorts without being prescriptive in terms of applied product development methodologies. After the first 4 sprints, we saw more engagement during these demo sessions, especially in language data, language models, and architecture. The sprints helped teams to plan and focus on a specific set of tasks, making the development process more manageable. They allow for more frequent feedback from stakeholders and the team, leading to faster adaptation and improvement.

Based on feedback we have received from the co-

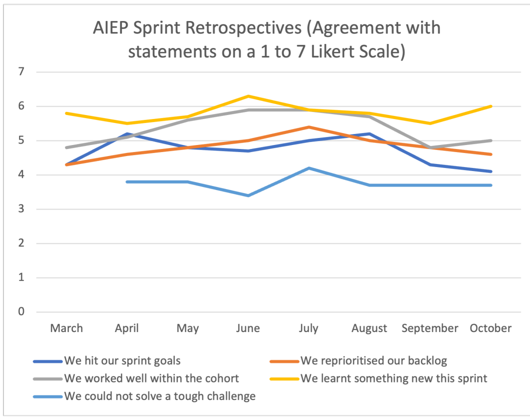


Figure 3: Results of monthly retrospectives of MVP development process

horts, the sprint review and demo sessions have been proven to be a very useful and productive tool for understanding bottlenecks, common challenges, and suggestions for improvement. As experience has been gathered with the format, various adjustments for the 2-hour virtual meeting have been introduced. Short collective retrospectives to gather feedback for further improvements with Menti and other virtual collaboration tools work well for larger scale development teams and quick retrospectives. Sample results are available in Figure 3.

4.2 Consolidation

The MVP's aim to prove concepts of most but not necessarily all capabilities of the information exchange platform. Accordingly, one cohort invested more in the experimentation on language technology (e.g. dynAg, Digital Green & partners) whereas another cohort focused more on end user research (e.g. Tech4Her) or channel optimization (e.g. Viamo & partners). Overall, the iterations and trials implemented across the MVPs cover the AIEP capabilities comprehensively including automated personalization and omni-channel delivery of content.

The development effort consists of rounds of parallel work and consolidation and recombination phases. Typical workstreams that have been addressed in consolidation and recombination phases include commonalities of the system architecture, language AI and related experimentation with latest advancements, end user engagement, Monitoring & Evaluation or DPG road mapping.

Open-source and DPG projects often struggle with similar challenges, including legal and governance matters, collective product management. Especially governance and collective product management are key challenges that require targeted support during the consolidation phases.

The AIEP project convened 3 consolidation workshops, so called cohort gatherings. They took place between Feb 2024 and April 2025, two times in Nairobi and in Gaya, India respectively. Representatives from all four cohorts participated, sharing their progress on project development. Industry experts in data, monitoring and evaluation (M&E), product development, user research, and language technology provided valuable insights during dedicated sessions, fostering collaborative discussions.

During two cohort gatherings, field visits to farms in Embu County, Kenya and Gaya, India were conducted. This provided an opportunity for cohort representatives to engage directly with smallholder farmers and extension workers. The visits facilitated a firsthand understanding of the challenges faced by these farmers, including soil health, access to inputs, and market access. This real-world context informed the ongoing development of the AIEP applications, ensuring they are designed to address the most pressing needs of the target population.

After the first cohort gathering, the next level of relationship building, and trusted cooperation has been reached. Cohort commitment and cross-cohort collaboration have increased significantly. Expert advice from outside of AIEP's cohorts has been very well received.

One of the Nairobi gatherings also facilitated broader engagement with the Kenyan agricultural community. A dedicated networking event was organized, inviting government representatives from the Ministry of Agriculture and Livestock Development. This provided a platform for the cohorts to showcase their developing solutions through pitches to a wider audience.

Other occasions that have been used to exchange knowledge and learnings between the cohorts and the digital agriculture communities include a learning event with agricultural and DPI experts of the Gates Foundation, the ICT4AG conference[13], FAO's dialogue on digital agriculture and AI [FAO, 2025], the Agrifin Learning Event 2024[14], ITU's AI4Good summit 2025[15], the Africa Food Systems Forum or the CGIAR Science Week 2025[16]. In addition, AIEP has actively contributed to DPI in Agriculture initiatives like the Open Agri Network[17], Vistaar in India or One Net in Kenya and engaged in events on AI with governments.

[13] ICTforAg 2024 – Localizing Impact, see https://www.ictforag.com/
[14] See https://agrifinale.org/
[15] See https://aiforgood.itu.int/
[16] See https://events.cgiar.org/scienceweek
[17] See https://openagrinet.global/

5 Results and Findings

AIEP aims to develop MVPs for an open-source, AI-based and gender-sensitive agricultural information exchange platform piloted in Kenya and Bihar, India. These MVP's utilize Artificial Intelligence/Machine Learning (AI/ML) to a large extent and integrate data and technology assets from content and solution providers to make information available to low-literacy and low-digital skill groups, dynamically and personalized. Overall, the use cases implemented across the MVPs cover the AIEP capabilities comprehensively including automated personalization and omni-channel delivery of content.

The 5 MVPs represent the AIEP design criteria and distinguish from each other with functions and features. They are built on a similar high-level architecture with substantial differences in the details and configuration ranging from different channel and model choices, user flows, additions like denoisers and speech detection and content choices. The high-level architecture also abstracts from different tech stacks which were unified only partly given the duration and size of this project.

5.1 The Minimum Viable Products

5.1.1 Farmer.Chat (Digital Green, Karya, Gooey.ai)

Farmer.Chat is an AI-powered agricultural assistant developed for smallholder farmers in rural, low-literacy, resource-constrained environments. Its design is grounded in user-centered principles with a strong focus on accessibility, multilingual/multimodal interaction, and personalized agricultural knowledge. It supports seven languages (Swahili, Amharic, Hausa, Hindi, Odiya, Telugu, English) via text, voice, and image and offers personalized advice across 40+ crops based on local practices and needs. Farmer.Chat offers different end usage modalities and channels including a mobile app. WhatsApp and Telegram. It further incorporates multimodal communication through text, voice notes, and images, enabling users with varying levels of literacy, particularly users who find verbal or visual communication easier than text.

After onboarding, users choose a crop and ask specific questions. For instance, a user selecting "coffee" and asking about the "benefits of the Ruiru variety" receives tailored, comprehensive information such as yield potential and disease resistance. Responses include voice notes in local languages for non-literate users, fostering a deeper engagement. The system encourages ongoing interaction by suggesting related topics and follow-up questions, promoting a personalized conversational experience. To maintain a feedback loop for continuous improvement, Farmer.Chat incorporates a two-tiered feedback system. Quick ratings via thumbs-up/down allow for immediate evaluation of response quality, while detailed star ratings capture more specific issues like incomplete or irrelevant content along with optional freeform feedback.

The architecture of Farmer.Chat is designed to ensure scalability, flexibility, and the delivery of accurate, contextually relevant agricultural advice as shown in Figure 4. Its core consists of a robust Knowledge Base and a suite of AI modules that work together to process user queries and deliver tailored responses via different frontend modalities. The Knowledge Base Builder aggregates structured and unstructured agri-data (manuals, videos, policies) including real-time weather, pest info, and market data tools via APIs and processes it into searchable formats. AI Modules combine Retrieval-Augmented Generation (RAG) and a reasoning engine to provide accurate, conversational, context-aware answers.

5.1.2 Mshauri (Opportunity International, DigiFarm, Gooey.ai)

Mshauri is a WhatsApp Chatbot integrated with an AI workflow platform by Gooey.ai which will respond back to the Farmers questions from an existing knowledge base (Corpus) leveraging OpenAI. It's an iterated MVP initially custom built as a Retrieval Augmentation Generation (RAG)-based solution and has been first tested in Malawi with 150 users. The solution was designed for use by Opportunity Farmer Support Agents (FSAs) to easily and rapidly provide accurate answers to smallholder farmer questions using a WhatsApp interface in either English or Chichewa, with text or voice interaction, and even by sending photos. Gooey.AI leverages a public 'recipe' (AI workflow) originally built with Digital Green and built a prototype solution leveraging the same authoritative content but that also included local language Chichewa in addition to English. This same recipe was further leveraged to build a service in Kenya leveraging content sourced by DigiFarm and targeting farmers directly (vs the Malawi version which was focused on Extension users), see Figure 5 for the system architecture.

Gooey.AI provides the ability to rapidly stand-up new bot solutions in a variety of domains beyond Agriculture. As an orchestration platform, it can leverage a known set of 'golden questions and answers', test new frontier private and open source LLM's, speech recognition and text-to-speech AI models, RAG docs and agentic calls to search the web for prices, weather, etc. and integrate other API-based services such as location-based soil analysis from iSDA [51]. This means it can continue to take advantage of industry-wide improve-

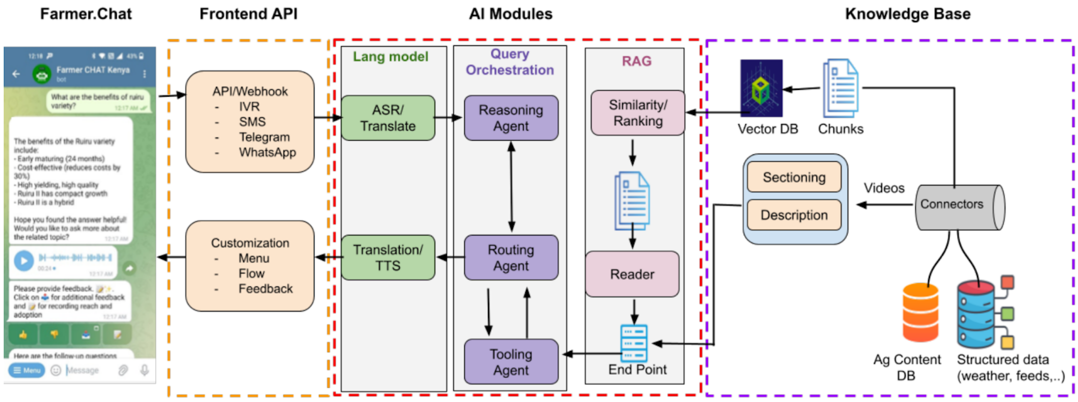


Figure 4: Overview of Farmer.Chat technical architecture

ments with a qualitative basis for assessing the best fit model and/or other components for customer needs. Additionally, Gooey.AI makes connections with communication channels such WhatsApp, IVR/SMS (via Twilio), Facebook plus embeddable widgets in mobile apps and websites. During the AIEP period, user interface affordances for photo, audio and location sharing, follow-up buttons, shareable QR codes and default questions (e.g. to make it easier for users to agree to the bot's terms) were added and iterated with the cohort's collective feedback and helped improve the bot's usability with farmers and extension agents.

5.1.3 Omnichannel Digital Assistant (Viamo, Producers Direct, HarvestPlus, Sahaj)

VIAMO, Producers Direct, Sahaj and HarvestPlus designed and launched a conversational omnichannel Digital Assistant MVP for smallholder farmers in local languages – English and Kiswahili in Kenya and in Hindi in Bihar, India. The Digital Assistant facilitates information access for farmers, particularly to improve capacities and skills in biofortified crop production (e.g. High Iron Beans and High Zinc Wheat). Information is made accessible via basic, non-internet mobile phones on a voice hotline and SMS service as well as a WhatsApp chat bot via text and voicemail for smartphone users.

Their system extends Viamo's IVR service through a combination of an LLM-based RAG pipeline to find and generate responses and speech-to-text (STT) and text-to-speech (TTS) technology to make incoming voice calls processable. RAG uses LLMs (GPT-4o and 4o-mini) and their embeddings (i.e. numeric representation of text) to create vector databases out of a knowledge database, validated by HarvestPlus, see also Figure 6 6 for the system architectur. Farmers can therefore call into dedicated lines that Viamo provides and instead of having to navigate the common but burdensome and very limited IVR menus, can ask their questions in natural languages. In Kenya, Viamo offers callback services to save users valuable airtime: User can call the number, the system then automatically ends the call and calls the user back. In addition, the cohort offers WhatsApp chatbot for user with smartphones.

Based on insights from user research, the cohorts substantially improved the style of the answers. The cohort started to compress context sent to the LLM leading to less irrelevant information returned and reducing LLM costs as prompt size declined.

Once users are onboarded, they select their preferred language (English / Kiswahili), listen to an introduction message and select their gender, ask their question after hearing a beep and press 1 and ask a follow up question or share their feedback.

5.1.4 dynAg (International Rice Research Institute (IRRI), CIMMYT, Gramhal, H3I, IFFCO Kisan, Dexian and Sumarth)

The dynAg platform is designed from the ground up, incorporating customized workflows, architecture, large language models (LLMs), and is available via the ai.sakhi app and IVR. Users can receive advisory on different value chains such as mushrooms, paddy, onions, as well as kitchen garden in the local languages Hindi, Magahi, Bhojpuri and Maithili. The dynAg team has undergone several trial-and-error loops to improve performance and usability of their platform. The team has made efforts to benchmark its models against commercial models such as GPT-4o which has been essential in identifying areas for optimization and ensuring the platform's performance remains competitive and scalable. For example, starting with the ChatGPT 2 LLM, dynAG has since moved to Mistral and now to ChatGPT 4-o. In addition to GPT-4o, a query classifier, a gender classifier and a profanity filter

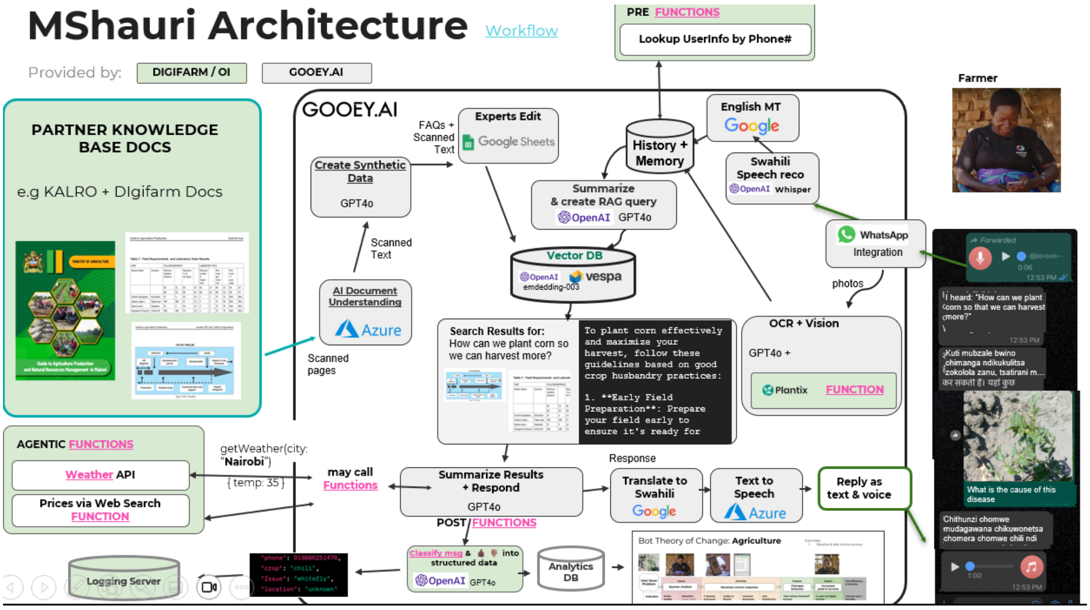


Figure 5: The system architecture of Mshauri

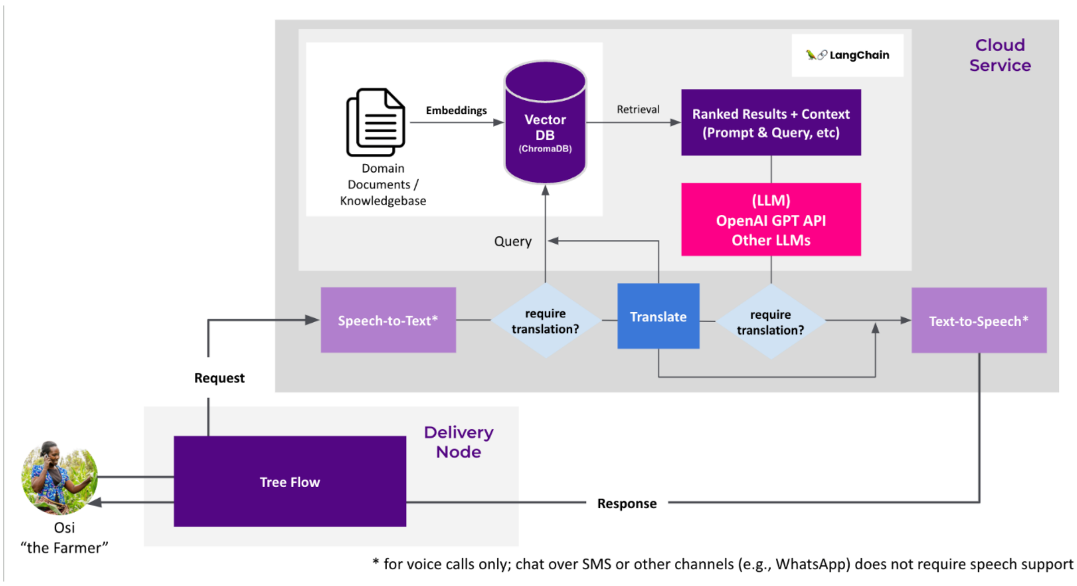


Figure 6: The system architecture of the omnichannel digital assistant from Viamo, Producers Direct, HarvestPlus and Sahaj

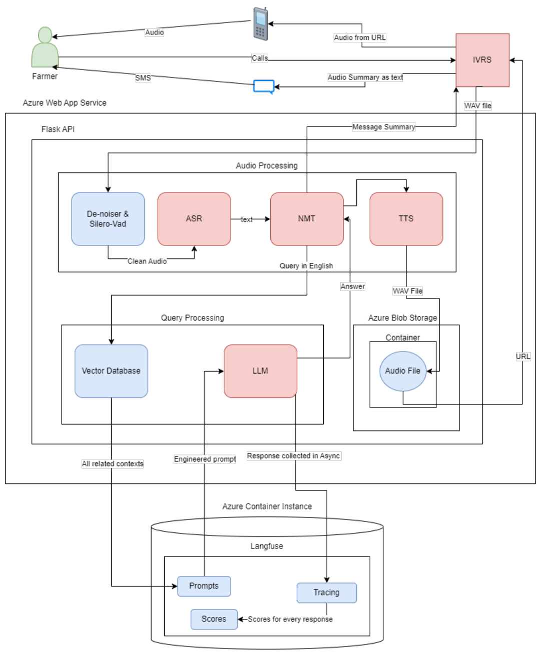


Figure 7: dynAg's system architecture for the IVR based system

was integrated into the advisory system to enhance the accuracy and user experience. Moreover, the cohort explored multiple open-source ASR models for speech-to-text conversion, focusing on Vakyansh for Hindi and Bhojpuri, and fine-tuned them using field-collected data to improve accuracy. This fine-tuning process enhances the model's ability to capture dialects and context, providing more tailored advisory responses. Models used include Vakyansh, Vasista, and a fine-tuned Whisper model, with a transformer-based seq2seq approach applied to better capture language-specific nuances. This has been essential for improving accuracy, particularly in gender classification and localized advisory content. To support farmers in low connectivity areas, offline features have been made available. For example, users with low internet connectivity will directly be forwarded to the IVR.

Integrating contextual data such as weather data and other contextual information has proven to make advisory responses more relevant and actionable. Storing user data, such as farm details, age, and gender, and offering personalized recommendations has made a tangible difference in how users engage with the system.

5.1.5 Tech4Her (Dalberg and DeHaat)

The MVP from DeHaat and Dalberg is an open-source architecture enabling customized, inclusive and interactive information exchange by last mile women farmers & extension agents, interoperable with omni-channels interfaces.

The solution has evolved through several versions, starting with DH 1.0 in February 2024, which focused on pest and disease identification using a quantized Llama 2 model with 70% accuracy and basic integrations on WhatsApp and WebApp. The next versions refined intent and entity identification, improved context retrieval, and reduced hallucinations and gender bias, with new API integrations and multi-language support (English, Hindi, Swahili).

The platform offers pest and disease management for over 40 crops, with RAG implementation integrating public and private sector data. It also includes API integrations for actionable insights, RLHF for optimization, and customization for gender roles. The architectural design for the project has made significant strides, with key components and infrastructure successfully integrated, laying a strong foundation for the system's core operations.

Critical modules such as the Bot Middleware Gateway have been established as the central hub for managing requests across various channels, including WhatsApp, Web App, and IVR/Call Center. The Request Splitter and Orchestrator Module efficiently directs user queries to the appropriate models and databases, ensuring seamless interactions. The ASR Engine, integrated with Speech-to-Text (STT), Auto-Correction, and Language Detection models, processes audio inputs and converts them into actionable text. The Intent and Entity Recognition Module accurately interprets user queries, while the Response Synthesizer provides versatile communication by converting outputs into either text or audio.

The solution also offers Text-to-Video Support in English and Hindi. Enhancements to the chatbot include text-to-video support in both English and Hindi, providing farmers with visual, step-by-step guides for various agricultural practices particularly as an integration of a soil testing text-to-video use case for extension agents. This feature will provide a visual and interactive approach to soil health assessment, enhancing the accuracy and effectiveness of advisories.

APIs have been developed for integration with other platforms, enabling B2B use cases, while data repositories like the Livestock DB and Language Data Repositories provide context-aware responses. External service integrations, such as climate data from IBM and financial services, are ready for deployment. A robust monitoring system has been put in place, including logging infrastructure and analytics dashboards (Tableau, Kibana, and Grafana) for real-time system performance and user interaction tracking.

5.2 The General System Architecture of the MVP's

The MVPs developed under the AIEP initiative were based on a shared high-level architecture, although each implementation varied in its specific technologies, AI models, and configurations. This architecture comprises two main components—an interface and a reasoning module—designed to be modular and interoperable, with programming interfaces structured to facilitate integration, see also Fgure 8. While this modularity allows flexibility across different communication channels, certain modules, such as those used in IVR systems, require specific adaptations like shorter, clearer responses.[18]

The interface component combines communication channels and speech technology to support speech-based interaction and multilingual access. It is designed to accommodate users with varying levels of literacy, hardware capabilities, and language needs. Farmers accessed services through telephone lines using IVR, SMS, smartphone apps, and messaging platforms like WhatsApp or Telegram, though not all MVPs supported every channel. The most effective approach combined smartphone channels for digitally literate users with IVR systems for those with feature phones, balancing reach and content richness. For IVR systems, a robust speech technology stack is essential, typically including automated speech recognition (ASR) and text-to-speech (TTS) systems. Enhancements like denoisers and speech detection models were used to improve ASR performance and reduce response latency.

Multilingual functionality in the MVPs primarily relied on machine translation since most reasoning components were English based. Some cohorts, such as Viamo and Sahaj, developed multilingual RAG systems to better incorporate Swahili-language agricultural texts. While machine translation currently operates as part of the interface, there is potential for it to be integrated with the reasoning modules as language model capabilities evolve.

The reasoning component of the system is designed to generate accurate, relevant, and user-friendly responses to farmers' queries. It typically includes a large language model (LLM), an optional query orchestration and classification module, connections to external data services (such as weather, soil, or market data), and a knowledge base. The classification module is commonly used to direct queries to the appropriate resources. As LLMs grow more capable, these functions may be integrated into a single model, enabling automatic information retrieval via protocols like Model Context Protocol and potentially consolidating speech and translation tasks as well.

Despite the increasing capabilities of LLMs, most cohorts adopted the RAG approach for greater control and factual accuracy. RAG combines an LLM with a retrieval system to ground outputs in verified external documents, ensuring contextual relevance and reducing hallucinations. Cohorts also enhanced responses by incorporating external data sources such as weather forecasts and soil maps, typically facilitated by the classification module. The knowledge base, essential to the RAG framework, required significant manual work to compile and validate content from institutions like CGIAR, KALRO, and various government agencies. This process remains time-consuming and has led to duplicated efforts across cohorts, emphasizing the need for better data sharing and collaboration.

From the user access perspective, the AIEP cohorts observed that while popular digital platforms like WhatsApp facilitated engagement among digitally literate users, reaching marginalized populations—such as elderly or less literate farmers—necessitated the use of telephone-based systems. This affirmed the importance of a multi-channel approach tailored to local realities. Language technology was also pivotal in expanding access, yet significant barriers persist for lower-resourced languages like Kikuyu and Bhojpuri. Technical and operational challenges, including the absence of standardized scripts and digital resources, hinder effective service delivery in these languages. Even commonly used languages like Hindi present issues, as agricultural terms are often misinterpreted by machine translation systems due to pronunciation or spelling variations, leading to inaccurate responses. While current systems perform well in high-resource languages, inclusion of minority language speakers remains limited without targeted investments in language data and model development.

On the backend, building relevant, localized knowledge bases posed a major challenge due to the dominance of English-language content. While translation helped, it did not address the lack of localized agricultural guidance. Curating, validating, and updating this content is an ongoing, labor-intensive task. The fragmented state of agricultural data also led to repeated efforts across teams. While LLMs offer promising capabilities, they come with risks such as factual inaccuracies and hallucinations. RAG was seen as a best practice for mitigating these risks and enhancing trust in the system. As AI-based agricultural advisory continues to evolve, ensuring factual correctness and minimizing harm will become increasingly critical, especially as governments scrutinize the reliability of

[18]The following description is based on our in-depth discussion of the architecture in AIEP Initiative et al. [2025].

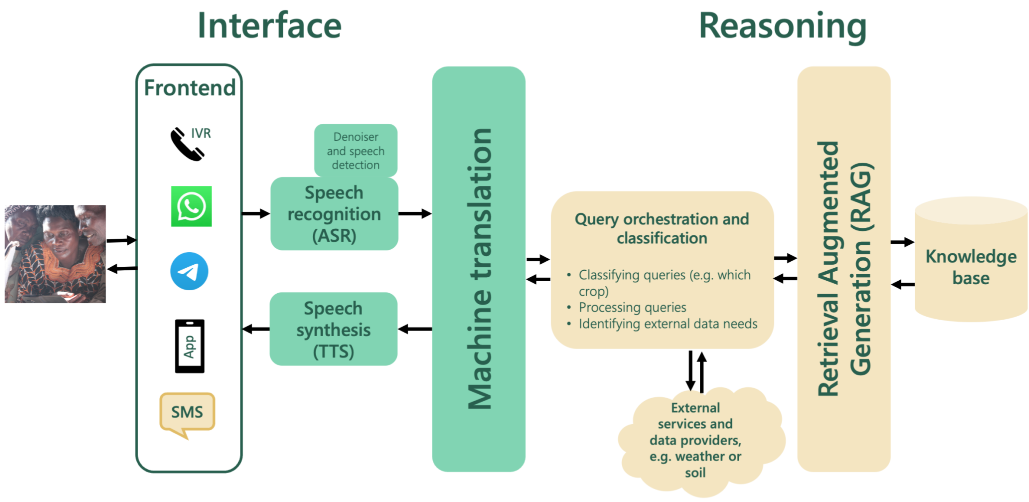


Figure 8: Common high-level architecture of AIEP MVPs (Source: AIEP Initiative et al. [2025]

AI-generated advice.

5.3 Golden Q&A and benchmarking LLMs for agriculture

As large language models (LLMs) rapidly advance, there is a growing need for reliable methods to evaluate their effectiveness in agricultural advisory services, particularly for smallholder farmers. To address this, AIEP developed a ”Golden Q&A” dataset—collections of expert-validated question-and-answer pairs drawn from real user queries and agronomist input. These serve as benchmarks to assess and compare LLM responses in a structured and standardized way, see Figures 9 and 10. This section summarizes this work, a more extensive discussion is available in AIEP Initiative et al. [2025].

The development involved partners such as Digital Green, which focused on leveraging similar golden Q&As in reinforcement learning with human feedback (RLHF) workflows, while other partners concentrated on designing evaluation strategies. The dataset was built by agronomists in India and Kenya and includes 114 open-ended questions (in English), reflecting realistic agricultural challenges. The questions came from two sources: common practice questions identified by agronomists, and frequently asked questions from 28,896 user submissions across the AIEP MVPs. Due to concerns about data leakage, the dataset is not publicly released.

A major challenge in creating and evaluating these questions is the high degree of context needed — factors such as weather, soil, and farm practices greatly affect the correctness of any given answer. This makes it hard to define a single ”correct” response and complicates model evaluation. To supplement the open-ended questions, multiple-choice questions (MCQs) were created for easier automatic comparison. These included more complex MCQs focused on sequences of agricultural actions, which LLMs handled better, although this area needs further exploration.

For evaluating LLM responses to the open-ended questions, AIEP tested several automatic metrics: word similarity (e.g., n-gram cosine, Jaccard), semantic similarity via embeddings, and using other LLMs as evaluators (”LLM-as-a-judge”). In addition, the agronomists assessed LLM responses based on factual correctness, comprehensiveness, relevance, intelligibility, and actionability for smallholder farmers. While semantic and LLM-as-a-judge approaches outperformed simple n-gram matching, only the LLM-as-a-judge method showed a statistically significant low to medium correlation with human agronomist evaluations across various metrics (for details, see AIEP Initiative et al. [2025]). Overall, LLMs performed well, but automated metrics largely failed to align with human judgment—highlighting the limitations of current evaluation techniques. For evaluating LLM responses to the open-ended questions, AIEP tested several automatic metrics: word similarity (e.g., n-gram cosine, Jaccard), semantic similarity via embeddings, and using other LLMs as evaluators (”LLM-as-a-judge”). In addition, the agronomists assessed LLM responses based on factual correctness, comprehensiveness, relevance, intelligibility, and actionability for smallholder farmers. While semantic and LLM-as-a-judge approaches outper-

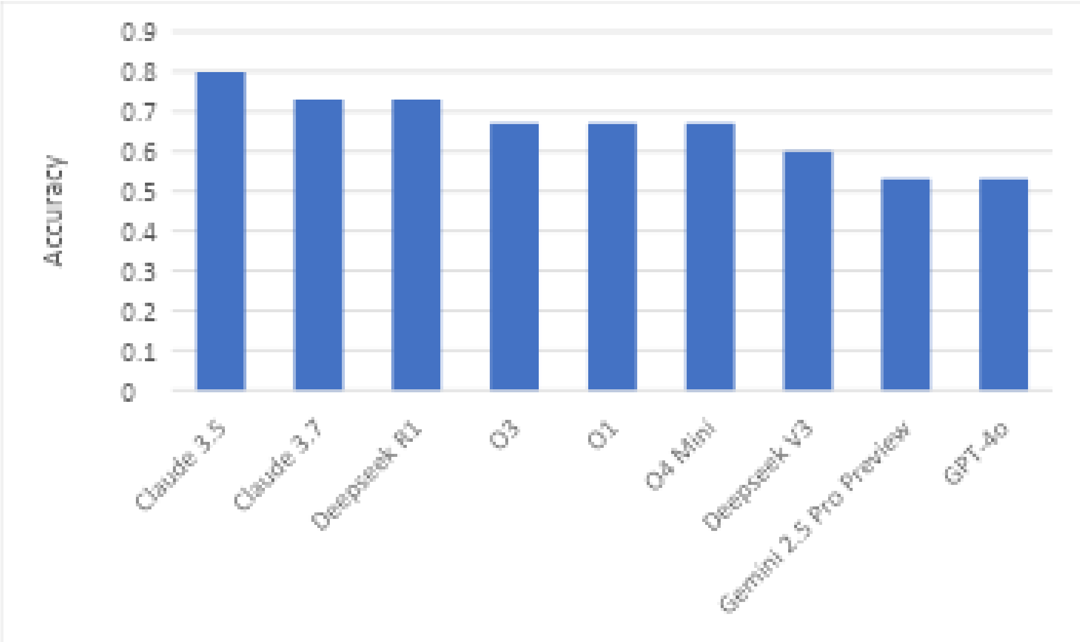


Figure 9: LLM performance on agricultural multiple-choice questions

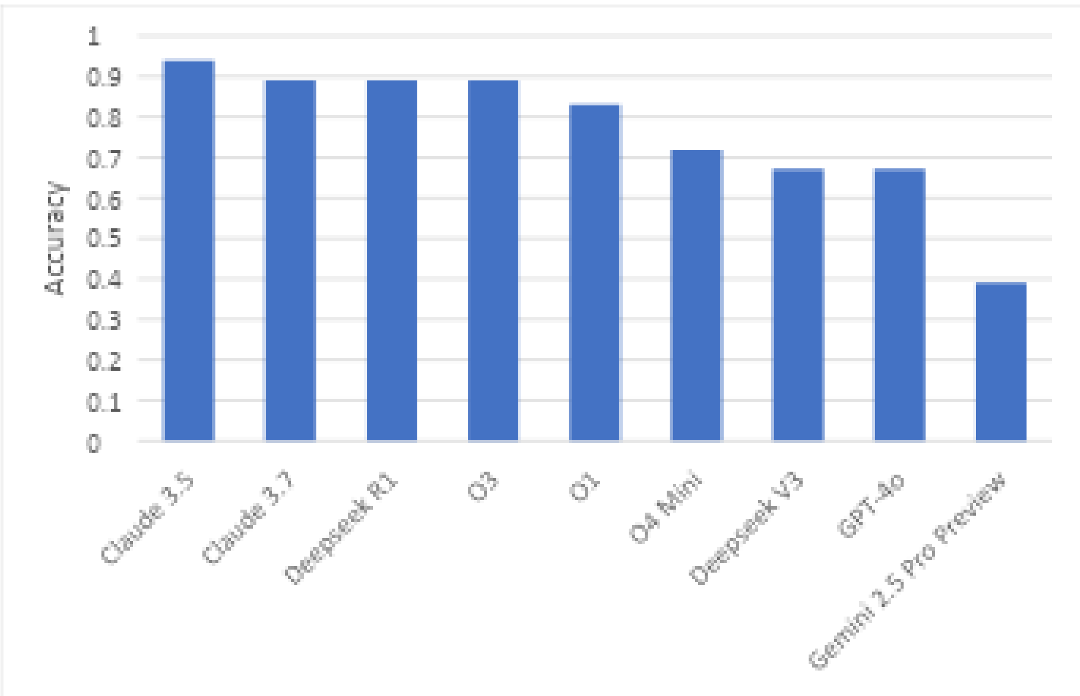


Figure 10: LLM performance on harder, action-sequence multiple choice questions

formed simple n-gram matching, only the LLM-as-a-judge method showed a statistically significant low to medium correlation with human agronomist evaluations across various metrics (for details, see AIEP Initiative et al. [2025]).

While Golden Q&As offer a promising framework for benchmarking LLMs in agriculture, significant challenges remain. These include dealing with the contextual nature of agricultural knowledge, developing more effective evaluation metrics, and expanding datasets to reflect real-world difficulty levels.

5.4 DPG's as common enablers

The AIEP initiative promotes collaborative approaches to developing AI-based advisory services by identifying and investing in key enablers that support the broader ecosystem. Accordingly, AIEP complied with the widely supported DPI strategy and approach and incentivized the development of DPGs as a basis for DPI based services. The cohorts have named different challenges while developing DPGs, particularly, the dedication necessary to maintain DPGs end to end as well as lack of understanding on DPG standards and registration process, e.g. according to DPGA[19]. To tackle these challenges, all cohorts have integrated a focused DPG roadmap including to make modules available as open-source and register them as DPGs.

As part of the MVP development process the project has identified 4 enablers—data sharing infrastructure, a common corpus, benchmarking and evaluation, and better language technology— as foundational components that should ideally be provided as DPGs to be integrated in country led DPI initiatives to foster open, equitable development.

- Data sharing is often hindered by inconsistent standards, limited resources, and weak incentives. AIEP piloted a customized platform extending Digital Green's open-source FarmStack to standardize data sharing, aiming to reduce duplication and promote collaboration. This included the creation of a unified interface for AIEP cohort members and other interested organizations to allow pooling and sharing of data resources, thus enabling a one-stop solution that supports AI model creation and delivery of last-mile services. Still, incentive issues remain and will require trust and agreement on what data should remain public or private.

- A common corpus of curated, high-quality agricultural knowledge is another major enabler. AI systems benefit from such centralized resources, especially when tailored to local needs through Retrieval-Augmented Generation (RAG) systems. The GAIA project exemplifies efforts to streamline access to this data. Tech4Her has developed a comprehensive collection of vectorized datasets. The integration of these datasets is aimed at facilitating enhanced agricultural advisory services, enabling better decision-making for farmers, agribusinesses, and government agencies alike. dynAg provides large datasets of crop extension and language data, including dialects such as Bhojpuri, Maithili and Magadhi.

- Language technology improvements, especially for low-resourced languages, are critical. Localized AI models need better vocabulary, contextual reasoning, and multilingual support. Projects like Digital Green's, Karya's and Gooey.ai's Gikuyu ASR, which used community-sourced voice data to train a high-quality speech recognition model with a WER 6%, show what's possible through collaboration—but also highlight challenges like diacritic inconsistencies and lack of standardized scripts. In addition, Karya optimized the Gikuyu ASR model reducting the latency to less than 3 seconds. dynAg developed a gender-specific classifier trained on 1,500 voice data samples that identifies the gender of callers to provide gender-specific agricultural advice. Secondly, the cohort trained a robust query classifier on 6,000 call logs from the IFCO KISSAN platform that categorizes farmers' queries by topic and provides accurate and tailored advice.

- Lastly, benchmarking and evaluation for these technologies are underdeveloped, particularly in low-resource settings. AIEP has initiated efforts like the Golden Q&A dataset to fill this gap. Better evaluation tools would help select and improve AI models, enhancing advisory service impact and guiding future investments.

Apart from the 4 foundational components, additional parts of the cohorts' MVPs have been published openly to foster collaboration and continuous improvement. For example, Digital Green publishes key components of their Farmer.Chat tech stack on GitHub[20] and shares findings openly (see Singh et al. [2024]). By publishing these components, the aim is to help foster a collaborative environment where AIEP cohort members and other agriculture and tech ecosystem actors can engage with and refine the tools, ultimately creating more effective solutions for small-scale farmers.

[19] See https://www.digitalpublicgoods.net/standard

[20] https://github.com/digitalgreenorg

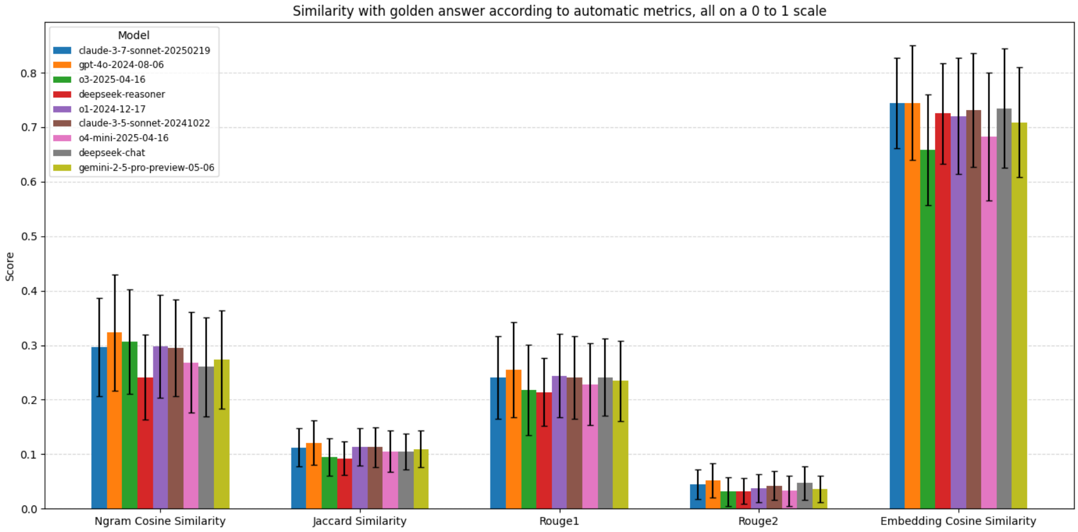


Figure 11: LLM performance on agricultural questions as rated by different automated metrics. Source: AIEP Initiative et al. [2025]

5.5 Digital Public Infrastructure

Smallholder farming systems face highly fragmented content and data ecosystems, which impede the organization and accessibility of foundational AI models (e.g. publishing and licensing of AI training data). Emerging digital public infrastructure (DPI) initiatives, such as Vistaar, OneNet, and Open Agri Network, aim to establish trusted networks that integrate digital agricultural components, advanced identity management, and data-sharing protocols. Although in their infancy with only limited implementation (agreed upon standards, protocols, sandbox availability etc.) these initiatives hold promise for addressing challenges such as data access, language technology advancement, and interoperability. Despite slowing initial MVP development, open approaches (DPGs and DPI's) deliver long-term benefits and require targeted incentives to foster collaboration.

The Open Agri Network[21] is a digital public infrastructure (DPI) initiative that leverages Artificial Intelligence (AI) to facilitate seamless interactions between farmers, agri-tech providers, financial institutions, and government services. By providing an open, decentralized foundation, OAN fosters agricultural innovation, enhances transparency, and reduces dependence on proprietary technologies.

OAN's role as a foundational digital infrastructure revolves around four key areas:

- Developing Open and Interoperable Technology - OAN provides a Beckn-based network layer and open-source AI infrastructure that enables real-time updates, personalized recommendations, and multilingual interactions.
- Supporting National Implementations - OAN works with governments in Africa and India, providing Digital Public Goods (DPG) toolkits to integrate its infrastructure into national agricultural strategies.
- Facilitating Global Collaboration - OAN fosters a global stakeholder network to promote open-source compliance, scalable AI strategies, and impact-driven monitoring.
- Enabling Policy and Governance Frameworks - OAN advocates for responsible data governance, inclusion, and transparency, helping policymakers design interoperable, privacy-preserving, and farmer-centric regulations to support digital agriculture ecosystems.

AIEP play an important role in strengthening OAN, for example in terms of multilingual AI capabilities.

- AIEP cohorts have curated local language datasets and developed open-source AI models tailored for Indian and Kenyan languages.
- Since AIEP's AI models are modular, they can be seamlessly integrated into OAN's intelligence system to enable multilingual interactions for farmers.
- The AIEP Data Management Interface can act as a central aggregator for these datasets, effectively serving as the AI infrastructure layer for OAN.

[21] See `https://openagrinet.global/`

By leveraging AIEP's contributions, OAN ensures inclusive access to agricultural knowledge across diverse linguistic and regional contexts.

There is a need to think of ways to connect various platforms in agriculture and to unify existing systems as no one system can solve all for all challenges. Initiatives like Open Agri Net aim to enable open and decentralized Digital Agriculture Grids that are underpinned by a universal suite of open protocols and data standards. Open Agri Net, Vistaar, One Net and other DPI initiatives can benefit from AIEP learnings and assets/outcomes. However, government channels are very complex and coordinating between so many players requires dedicated investments.

Experiences in Ethiopia and other regions highlight the limited capacity and technical expertise of governmental organizations to adopt such innovative solutions. Alternative approaches, such as the Project Management Unit (PMU) model piloted by Precision Development (PxD) in Ethiopia and India, offer promising avenues to address these capacity gaps [Precision Development (PxD), 2025]. However, government partnerships alone may not suffice for sustaining AIEP; a broader ecosystem approach, incorporating public-private partnerships (PPP's) and private sector consortiums, could enhance scalability and viability. Countries like Nigeria and Zambia exemplify contexts where this approach might prove fruitful.

It's the right combination of centralized innovations and technical advancements of common interest and country led implementation that are customized according to the local context. AIEP's Kenya and India engagement could also serve as good practices for country technical assistance applicable to agricultural advisory as well as other use cases and sectors.

5.6 Monitoring & Evaluation

AI based advisory solutions are still new and have been deployed for a short period of time with a limited number of end users. Accordingly, standardized evaluation metrics or rigorous impact evaluations are missing. PxD recently developed a flexible, user-centered framework to rapidly assess AI agricultural advisory tools, combining foundational model evaluation (e.g. LLM performance), content accuracy, usability, and product assessments [55]. The goal is to help governments and partners determine which tools are scalable, equitable, and ready for impact before investing in costly Randomized Controlled Trials.

The early stage of experimentation with limited end usage and a high amount of adaption, pivots and iterations conflicts with the needed constant intervention for a rigorous impact evaluation of the MVPs. In line with PxD's evaluation framework AIEP applied various interventions to monitor and evaluate the MVP's on (technical) performance, accuracy and relevance of content, usability and user satisfaction as well as product stability, adaptability and scalability to assess and compare the individual MVPs:

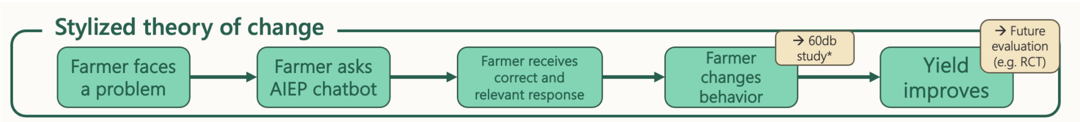
- a standard indicator framework including usage indicators (number of active users, retention rate, gender distribution of usage, number of questions per user, user satisfaction score etc.) technology and MVP development related indicators (channels, languages, models tested, utilization of data etc.), see Figure 12
- an end-user study applied across all cohorts to understand the user experience of the AIEP MVPs and to compare the experiences of farmers and agents using these different services. The survey has been conducted with more than 800 users via phone interviews of randomly selected users from the cohorts' contact databases.
- cohort specific end user interaction and evaluation based on field visits and observations, interviews etc. as well as logs and system usage analytics, e.g. in terms of most commonly asked questions, gender disaggregation etc.
- development of a set of golden Q&A pairs to be able to assess foundational models quickly. These golden Q&A pairs stem from real world usage paradigms from our end usage pilots (see above).

At least a subset of the standardized indicators has been collected across all cohorts, see Figures **??** for examples. The cohorts started to report in sprint no. 6 on these standard indicators during the monthly sprint and demo session. These metrics have been steadily improving; however, some cohorts have had quite significant changes (also temporarily declining metrics) due to adding new content or user-onboarding campaigns.

Introducing these standard indicators has allowed for better objective tracking and comparison of cohorts, however, the latter should be considered with care as some cohorts have been working on this solution longer than others (e.g. Digital Green).

5.7 End user engagement

End user orientation and regular engagement has been one of the design criteria of AIEP from the very beginning. Accordingly, the cohorts applied end user engagement methodologies on their own as well as collectively (see chapter on End User Research). Some of the cohort's individual end user



	User indicators (all disaggregated by gender)					Tech indicators		
Indicator	# of active weekly users	Retention rate (active users/total users)	% of successful advisory**	User satisfaction score	Most commonly asked questions	RAGAS metrics	# agricultural content sources	Cost per session
How to measure?	Active users = at least on question asked	See active users	Share of responses not answered by 'I do not know', *by channel and language*	# of weekly thumbs up/# of active weekly users***	Aggregated by common topic	Faithfulness, context precision and answer relevancy	Confirmed by list of agricultural content sources	Including channel, API, and infrastructure costs by country
Monitors	Farmer asks AIEP Chatbot	Farmer asks AIEP Chatbot	Correct and relevant response	Correct and relevant response	Correct and relevant response	Correct and relevant response	Correct and relevant response	Long term sustainability

Figure 12: Stylized theory of change and AIEP Standard Indicators

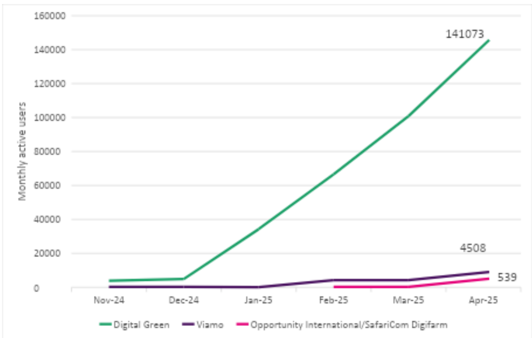


Figure 13: Monthly active users in Kenya and Bihar of AIEP MVPs by Digital Green, Viamo and Opportunity International/Safaricom Digifarm (whose active user numbers have grown to 912 by early June)

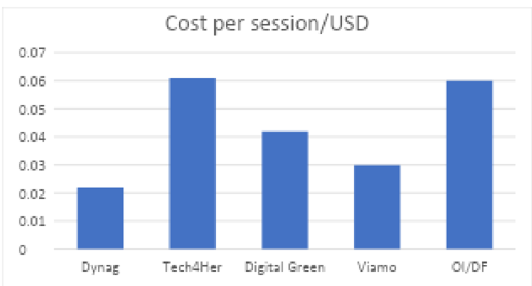


Figure 14: Standard indicator reporting of cost per session in USD as of April 2025 per cohort

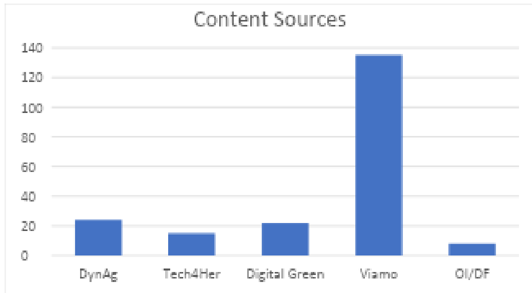


Figure 15: Standard indicator reporting of content sources as of April 2025 per cohort

research include the identification of control groups for user testing, Human Centered Design research and synthesis, user feedback ratings on the quality of service etc.

As an example, during implementation of the Omnichannel Digital Assistant (Viamo, Producers Direct, HarvestPlus, Sahaj) in Kenya and Bihar, farmers were engaged through on-ground training sessions conducted by HarvestPlus. The sessions helped introduce the Digital Assistant tool and offer guidance on how to interact with the platform. The table below summarizes key user engagement barriers encountered during rollout, the lessons learnt, and the strategies implemented in response.

5.8 End user research

To accompany the quantitative monthly metrics and to assess the MVPs from an end-user perspective, 60 Decibels (60db) conducted an end-user study in Q1 and Q2 2025 with 824 farmers (38% women) and 20 agents across all cohorts. The study included a quantitative phone survey in multiple languages as well as qualitative interviews to confirm information and gather in-depth insights from agents. The overall goal of this study originally focused on providing a third-party comparison of the

Barriers	Lessons Learnt	Response Strategy
Perceived Cost	Farmers were hesitant to use the tool due to fear of call and data charges.	Proactive communication that the service is free through SMS and at the beginning of each IVR call.
Lack of Awareness	Many users were unfamiliar with the service or unsure how to engage effectively.	Provided on-ground training (via HarvestPlus), trained extension workers, and included clear UX instructions at the start of IVR calls and through SMS.
Phone Sharing Practices	Shared phone access, especially in households, meant some intended users might not receive timely messages.	Sent repeated SMS reminders to mitigate missed engagement opportunities due to shared device use.
Digital Access Gap	Many users do not own smartphones or have internet access.	Selected IVR as the primary channel, as it works on basic feature phones and requires no internet.
Unfamiliarity with Hotline	Farmers were unsure of what number to call, affecting inbound engagement.	Sent SMS messages with the hotline number, encouraged farmers to save it, and distributed printed flyers.
Language and Literacy Barrier	Users with low literacy struggled to engage with text-based or app-based solutions.	Chose IVR over apps like WhatsApp; IVR requires no reading or digital literacy, making it more inclusive.

Table 1: Barriers to use of AIEP MVPs, lessons learnt and response strategies

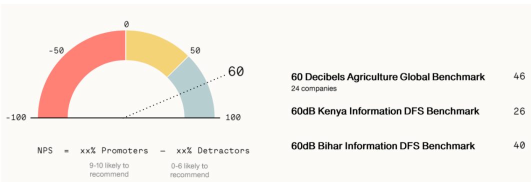
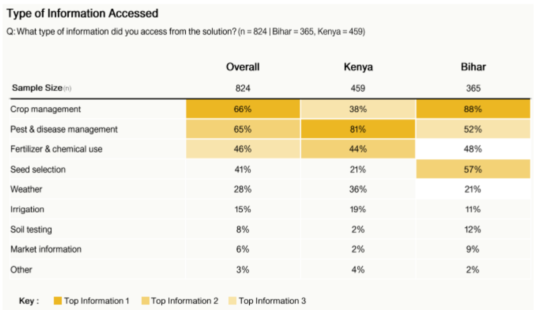


Figure 16: Net Promoter Score (NPS) of AIEP solutions and relevant benchmarks



Type of Information Accessed

Q: What type of information did you access from the solution? (n = 824 | Bihar = 365, Kenya = 459)

	Overall	Kenya	Bihar
Sample Size (n)	824	459	365
Crop management	66%	38%	88%
Pest & disease management	65%	81%	52%
Fertilizer & chemical use	46%	44%	48%
Seed selection	41%	21%	57%
Weather	28%	36%	21%
Irrigation	15%	19%	11%
Soil testing	8%	2%	12%
Market information	6%	2%	9%
Other	3%	4%	2%

Key : Top Information 1 Top Information 2 Top Information 3

Figure 17: Insights on information accessed by end users

solutions but during the MVP development, we realized that the cohorts progress, in part due to their different starting points, was very different while also more investment is needed before a single best solution could be picked for further scaling. Therefore, the goal of the study shifted towards benchmarking with other data to gain insights on the potential impact of AI-based advisory and to create third party assessments to inform our and the cohorts' further actions.

AI-based advisory. The net promoter score (NPS) as a measurement of satisfaction is 60 on average, an excellent score and clearly exceeding global (46), Kenyan (26) and Bihar (40) benchmarks by 60db. Importantly, women report a higher NPS than men. The qualitative interviews indicated that farmers often share information received from the AIEP solutions with peers and encouraged them to also use the solution. In addition, farmers reported in the qualitative interviews that they assume their peers to respond truthfully.

On areas for improvement, the completeness and relevance of the information provided stands out. It is the major reason why farmers would not recommend the solutions to others. In addition, 50% of those who reported that they hadn't applied the information provided reported that unavailable inputs or financial constraints kept them from taking action. This indicates again that the information provided is not always sufficiently tailored to the context and that AI-based advisory in addition to information will need integration with other services that alleviate constraints. Unsurprising yet concerning is as well that farmers with lower education levels reported at a higher likelihood that information was not easy to understand (overall 33% of farmers), pointing to further work required to fulfill our original goals of providing solutions working for all smallholder farmers.

This study provides first encouraging data points but will need to be complemented with further studies in the future. Like most studies, this showed some potential limitations. For example, the educational attainment is higher than the average smallholder farmer, with 30% of the survey participants reporting a university, polytechnical or other higher degree.

78% of the survey participants also reported to have a smartphone, potentially indicating a selection bias. In implementing the survey, 60db also uncovered challenges with name and brand recognition for most cohorts as a substantial number of users called (meaning their numbers were recorded as having used the service) did not recall the AIEP solutions by name or description. While not affecting the utility of the solutions themselves, this posed some challenges in implementing the survey and made larger numbers of phone numbers called necessary.

Despite the limitations, the 60db study suggests AI-based advisory has strong potential. Farmers seem satisfied with the solutions, stressing their availability and quality of information. The next step which various partners of the AIEP initiative now are preparing are rigorous evaluations of the impact on yields and livelihood to show the material benefit of the solutions.

5.9 Lessons learnt

There are four major areas of learnings that cut across the various topics described above:

5.9.1 Clear goals with clear indicators

AIEP at its core was an experimental and exploratory project and part of the Gates Foundation Learning Agenda on Digital. Experiments and exploration creating learnings on information exchanges and AI-based advisory was the clear goal of AIEP. To encourage experimentation and in absence of knowledge, we consciously refrained from being prescriptive when guiding the cohorts, not providing too much guidance on user number goals or priorities among challenges. As we learnt through implementing the initiative, our priorities shifted as well with insights and new developments.

While it would have been difficult to set clear goals (e.g. achieving a user number of X) in the fast pace of the beginning, we think that clear goals and attached clearly defined indicators would have held the potential for further insights. For example, reaching as many users as possible and being as inclusive as possible is a trade-off in practice. Different cohorts decided differently how to resolve this trade-off but this was not always clearly discussed.

AIEP itself also in part faced the challenge of aiming at exploring various topics at ones ranging from leveraging language technology for better access to collaboration and exchange for better advise. This large number of potential areas of interest at times spread our attention thin, and future initiatives on AI-based advisory should rather leverage a clear division of labor with different projects working on clearly defined goals while some implementers focus on integrating the outputs of those initiatives with the aim of reaching a maximum number of smallholder farmers with a minimum of quality and inclusion (e.g. share of female farmers). We perceive initiatives like GAIA and the ongoing discussions around a global AI Facility as the right steps in this direction.

5.9.2 Difficulties in collaboration

Collaboration was at the core of AIEP and its facilitation a key part of GIZ's role as an anchor partner. We achieved a substantial amount of collaboration through the monthly meetings, gatherings and workstreams which the cohorts stressed as a key part that made AIEP useful for them. However, we also experienced that collaboration requires work and faces obstacles. Funders usually encourage or even require demand between grantees and the development sector usually upholds norms of cooperation and collaboration to achieve the commonly shared Sustainable Development Goals. However, grantees nevertheless are in partial competition to each other, especially since the recent funding cuts in international cooperation. This competition also was implicit in AIEP with the early outlook that there might be follow-up funding for which the most successful solutions might apply. In addition, the cohorts also were tasked to build similar solutions, to explore different approaches, but this strengthened competition rather than encouraging a division of labor.

In theory, division of labor would be beneficial for cohorts even in this setting, given that we demanded that major pieces were made openly available among cohorts. If another cohort developed or found a superior solution, sticking to one own's instead of focusing scarce resources on one's specialties or other opportunities seems inefficient. However, this is not what we observed. Despite our constant encouragement, we struggled to deepen collaboration beyond exchange of insights on a reliable basis. The differences in tech stacks and implementations might have contributed to this, but we also assume that a sense of competition hindered taking up other cohorts' solutions.

There is no easy solution to this. We assume that a clearer division of labor and clear goals might contribute to better collaboration. In addition, creating easily usable components likely requires more resources than were available beyond the ongoing iterations and MVP development.

5.9.3 Product and team management: Tech projects with grants

We and the development sector overall look towards best practices in industry when developing technology to solve problems in agriculture and beyond. However, the structure and existing expertise of the sector pose some challenges to adopting those practices. We have observed two key challenges:

- Grants with their required proposals, objectives and budgets at times are at odds with the staffing requirements to implement proper agile methodologies. Grants usually require grantees to spell out their project, approach and solution in the beginning. While those proposals are not completely binding, and we treated them liberally to allow the cohorts the flexibility needed, they nevertheless constitute a binding part of a contractual agreement. The funding structure of most of our partners also leads them to allocate their staff to multiple projects at the same time and forces them to combine different funding streams to fund their staff's position. This often leads to large teams working on individual projects. Instead of this common situation, it might have been better to ask cohorts to commit a certain percentage share of their team (e.g. 50% of an engineering team with one product manager) for the duration of the time with limited resources reserved to acquire additional service needed. Our selection project then should have rather focused on the quality of those teams, existing solutions and to a lesser degree than we implemented the quality of their proposal.
- In addition to the obstacles coming from usual funding arrangements, product management is a key shortage in the development sector. While a clearly and common defined position in industry, many partners in the development sectors do not have dedicated roles covering product management, implying that people cannot build up experience with the challenges of implementing product management in a development sector setting. Many of the AIEP partners are in fact an exception to this, but we assume that keeping this role in mind will be very important for future initiatives. In addition, social enterprises or partners with strong private sector links are also leading the development sector in product management.

6 Conclusion & recommendations

The AIEP initiative has proven the concept of Gen AI based advisory services for smallholder farmers. Notably, it has facilitated the development of functional MVPs for an omni-channel information exchange platform tailored to users with low literacy and digital skills. Through collaboration with five cohorts, several solutions have advanced to stages nearing market readiness, although critical challenges and open questions remain, necessitating further experimentation and refinement.

Whilst MVP's and early ME indicators look promising there are open questions and outstanding challenges to be tackled by donors and industry. Such questions include long-term business models and viability, central services common to all cohorts and MVP's or Service Level Agreements (SLA's) that qualify the solution for scaled roll-out in partner countries.

It's the right combination of centralized innovations and technical advancements of common interest and country led implementation that are customized according to the local context. AIEP's Kenya and India engagement could serve as good practices for country technical assistance applicable to agricultural advisory as well as other use cases and sectors.

Gen AI is one of the very few strategic areas in international cooperation that gains increased interest, investment and portfolio development. In addition, agriculture remains one of the key sectors to reduce poverty in LMIC's. The Gates Foundation, UAE and the Worldbank are amongst the organizations that are investing. Multilateral donor coordination mechanisms like the Agriculture workstreams of the AI4D funders collaborative (global) [56] or Digital Agriculture Roadmaps (local, national) help to synergize on funding sources and to coordinate implementation planning.

GF and UAE intend to establish a Global Facility for Generative AI-Driven Agricultural Advisory. This facility aims to harness generative AI, particularly LLMs, for delivering personalized, scalable, and locally relevant agricultural advisory services to smallholder farmers in low- and middle-income countries (LMICs). Key Objectives include to coordinate a global consortium to organize agricultural data, fine-tune LLMs, and promote open-source tools and ethical standards. It also serves as a trusted hub connecting AI innovation with agricultural development, including partnerships with Big Tech, LMIC governments, and international organizations.

On top of this Global Facility GF intends to provide in-country support for implementation in focus geographies (e.g., Kenya, Nigeria, Rwanda, Ethiopia, Indian states). These country-led implementations increase adoption & uptake of some of AIEP's results including the MVP's utilizing coordinated, open, and inclusive ecosystem. These validated solutions could come from the AIEP cohorts as well as other partners working on related system. Country led implementations build upon public-private partnership (PPP) frameworks to co-fund and support the deployment of these solutions.

The country implementation would focus on deploying market-ready components to a larger user base. Initial efforts could prioritize leveraging successful initiatives such as the Digital Farmer Services project in Bihar (Bihar Krishi), led by Microsave. The rollout process would establish PPP consortia involving governments, the ag industry, and financial institutions to share costs and provide co-investment opportunities.

As government partnership often offer promising pathways to scale, but those government partners at times lack the AI expertise to make informed decisions, we propose further investment in capacity building and supporting those partners.

This proposed framework builds on the digital public goods (DPG)-based product development. It represents an evolution of AIEP's cohort-driven approach by enabling shorter development cycles, fostering a collaborative community of practitioners, and integrating a Global AI Facility with innovative frontend applications. High-quality, validated components can be incrementally integrated through adherence to standards and protocols, ensuring compatibility with national, regional, and global digital public infrastructure (DPI) initiatives.

Acknowledgements

This work was supported by the Gates Foundation through the AIEP project (Grant Number INV-051386) and integrated with the German Federal Ministry for Economic Cooperation and Development (BMZ) funded initiative "FAIR Forward - Artificial Intelligence for All". The conclusions and opinions expressed in this work are those of the authors alone and shall not be attributed to the Gates Foundation or the BMZ.

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