FarmChat: A Conversational Agent to Answer Farmer Queries

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Farmers constitute 54.6% of the Indian population, but earn only 13.9% of the national GDP. This gross mismatch can be alleviated by improving farmers' access to information and expert advice (*e.g.*, knowing which seeds to sow and how to treat pests can significantly impact yield). In this paper, we report our experience of designing a conversational agent, called FarmChat, to meet the information needs of farmers in rural India. We conducted an evaluative study with 34 farmers near Ranchi in India, focusing on assessing the usability of the system, acceptability of the information provided, and understanding the user population's unique preferences, needs, and challenges in using the technology. We performed a comparative study with two different modalities: audio-only and audio+text. Our results provide a detailed understanding on how literacy level, digital literacy, and other factors impact users' preferences for the interaction modality. We found that a conversational agent has the potential to effectively meet the information needs of farmers at scale. More broadly, our results could inform future work on designing conversational agents for user populations with limited literacy and technology experience.

CCS Concepts: • **Human-centered computing → Interaction design**; **Ubiquitous and mobile computing**; • **Computing methodologies → Intelligent agents**.

Additional Key Words and Phrases: Chatbots, conversational agents, developing world, ICT4D, India, smartphone, agriculture, farming, audio-only UI, audio+text UI, user interfaces, speech-based interfaces, QnA system

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1 INTRODUCTION

According to the 2011 census, 54.6% of the Indian population is engaged in agriculture [10], but earn only 13.9% of the country's GDP [49]. To address this gross mismatch, the Indian government aims to double farmer incomes in the next five years [38]. It is well believed that access to information and expert advice is crucial in achieving this

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goal [5, 15, 16, 41]. Such information includes the choice of seeds to sow, how to combat specific crop diseases, weather forecast based advisory, and optimal harvesting times. However, farmers in rural India often have limited access to such information [15, 16, 41, 46]. Even when the information is available, farmers are often unable to consume it due to illiteracy, as India has the lowest adult literacy rate in the world [47].

Several solutions have been proposed to solve the limited information access issue faced by farmers in the developing world. This includes forums for asking questions to experts and peers [16, 41], peer education using participatory video [15], interactive voice response (IVR) systems [12, 43, 46], and social networks for farmers [27, 35]. Since 2004, the Indian government has been operating the Kisan Call Centre (KCC). The KCC [16] is a toll-free call-centre to answer farmers' queries in 22 local languages daily between 6 am to 10 pm. However, it is difficult for the manually operated call-center to keep up with the massive demand. In June 2014 alone, 1.11 million calls were received by the KCC, out of which over 450,000 (~40%) went unanswered [3]. Thus, it remains an open problem to build a system that satisfies the information needs of rural farmers. Systems meant to serve this population must be usable and acceptable by people with limited literacy, highly scalable, available around-the-clock, responsive, and have a manageable overhead for agricultural experts (referred as agri-experts).

As a potential solution, in this paper, we introduce an automated conversational agent, or chatbot, to provide farming related information through natural speech interactions. A chatbot offers several benefits that can potentially satisfy the above-mentioned requirements. First, speech is the most familiar mode of interaction that requires little learning or literacy. In fact, audio-based interactions are considered the preferred—sometimes the only usable—interactions for illiterate users [33, 34]. Interactions with an agent should enable farmers to formulate queries as if they were talking to another person. Second, conversational agent systems offer direct information access without the need to navigate complex information paths as often required by graphic user interfaces (GUI), and simplicity is considered a primary design requirement for low-literate users [33]. Finally, from a system point of view, a chatbot is a scalable solution that can be accessed by any user at any time. Moreover, agri-experts can review user inquiries to the chatbot periodically and then continuously expand the chatbot knowledge base without high maintenance cost.

While recently the HCI community has developed an increasing interest in conversational agents and demonstrated their benefits [20–22, 29, 30, 32, 44], most prior works focus on literate, technologically-advanced users. In our work, we take the conversational agent on the ubiquitous smartphone to rural farmers in the developing world, broadening its scope to a new demographic. This new user population and usage require answers to questions concerning (a) how to encode farming related queries efficiently in a conversational system; (b) the robustness of speech and language technologies in the local language; (c) the acceptability and usability of chatbot technologies for rural farmers; and (d) interaction modality preferences of the farmer population.

To answer these questions, we designed *FarmChat*, a conversational agent to meet the information needs of rural Indian farmers. Recent work suggests that interface design should support semi-literate users differently from illiterate users [13]. For semi-literate users, text can offer faster and unambiguous mode of interaction [13], while for illiterate users, the appearance of text negatively impacts their performance [34]. Further, text output allows more flexibility to process information and persistent access to messages, which we identified as a design requirement in a formative study. Hence, we built and compared two interfaces of FarmChat: (1) *Audio-only* (input: speech; output: audio) and (2) *Audio+Text* (input: speech, button; output: audio, text, image).

Currently, FarmChat supports Hindi–the most widely spoken Indian language–and answers queries about potato farming as a use case for the study. The knowledge base embedded within FarmChat on potato farming was derived by analyzing the query logs from KCC and a formative study with 14 farmers and 2 agri-experts. Thereon, we ran a task-based user study with 34 farmers in villages around the city of Ranchi in the state of Jharkhand in eastern India. From the 626 inputs provided by the participants, we found that farmers appreciated FarmChat's precise and localized responses, showed great interest and trust on the information, and generally found a conversational agent easy to use, thus hinting that a chatbot has the potential to meet their farming-related information needs at scale. We also uncovered some interaction behaviors and issues that are important to consider when developing chatbots for this user population, including over-expectation of chatbot's capabilities, a tendency to imitate phone conversations with a human, and unfamiliarity with standard speech input and messaging interfaces. Moreover, we found that literacy level, prior experience with technology, and profession played crucial roles in the users' preferences between the Audio-only or the Audio+Text interface. We conclude with implications for designing chatbots for low literate and novice technology users.

Our main contributions are: (1) Proposing a novel speech-based conversational system to meet the information needs of low literate rural Indian farmers, wherein the chatbot intelligence was based on KCC logs and inputs from local agri-experts. (2) Comparing two chatbot interfaces with differing interaction modalities, and inferring that preference for an interface was highly dependent on the farmer's literacy level and prior technology experience.

2 RELATED WORK

Our work is mainly informed by three areas of relevant research: UIs for low literate users, technologies to support agriculture related activities, and conversational systems.

2.1 UIs for Low Literate Users

Designing user interfaces for low literate populations is a growing area of research [13, 26, 33, 34, 40]. It spans multiple application domains, including agriculture [11], health care [18], citizen journalism [36], video search [11] and social networking [35]. Research has shown that users with low levels of literacy perform better with user interfaces which use minimal or no text and represent textual information using graphics/photographs and audio [33, 34]. Even interfaces that use graphics liberally, such as a job search web portal for illiterate users [34], rely on audio to provide descriptions and instructions. Voice as an interaction modality is well-suited for low literate users, as it is a natural means of expression. Voice-only citizen journalism portals [36], voice-based Q&A forums for rural farmers [41], and IVR systems [18, 25] are a few successful examples, relying heavily on speech for input and audio for output. With audio as the output modality, researchers have compared speech versus DTMF/keypad for input and obtained contrasting results with low literate users [18, 40, 45]. Interestingly, most low literate users are numerically literate; hence, using numbers (both for input in keypad buttons and output as text) has been found to be acceptable [34]. This has paved the way for multimodal interfaces [11, 35] that embed graphics, voice, and numbers for low literate users.

Recent research highlighted the interaction differences between illiterate and semi-literate users and suggested to treat the two groups differently in interface design [13]. Comparing them in tasks on Audio+Text versus Text-only interfaces, Findlater *et al.* [13] found that text was important for semi-literate users since it offers a faster and less ambiguous mode of interaction. Importantly, text allows for opportunistic language learning. Interestingly, social factor also results in the preference of a text-based interface since it avoids the stigmatized perception of illiteracy [26]. For illiterate users though, the appearance of text negatively impacts their task performance [13, 34]. Hence, we designed and compared two FarmChat interfaces: Audio-only and Audio+Text.

2.2 Agriculture-related Technological Solutions

ICT4D research has contributed immensely in developing technological solutions to help farmers in developing regions with their information needs [12, 15, 41, 43, 46]. Farmers are usually located in rural areas with low literacy levels; hence, a majority of the proposed solutions rely heavily on voice as an interaction modality. Two of the widely adopted approaches are automated calls providing agriculture-related knowledge and IVR systems. These are highly scalable solutions, but are limited to providing generic crop-related advice, which may not work for a majority of farmers due to variations in crop, soil type, climate, *etc.* Automated calls have been adopted by several governments around the world, including India's [37]. Khedut Saathi [39] took automated calls a step further, allowing farmers to forward the received audio message to five other phone numbers. IVR systems use a computer-based back-end with a keypad/voice-based input, and audio output to provide farmers with relevant information related to weather, fertilizers, and market prices [43, 46]. Accessing the hierarchical navigation is a major usability issue with IVR systems [33]. Instead of restricting their system to audio alone, Digital Green [15] focuses on creating videos by farmers and uses human-mediated instruction for disseminating these videos to other farmers. VideoKheti [11] proposed a multimodal method for illiterate farmers to search specific videos.

Other solutions offer custom advisory services to farmers. The Indian government program KCC [16] allows farmer to dial a toll-free number and get responses to their specific queries. Since the demand for such information is too large to be met by a manually operated system, most of the KCC calls go unanswered because the phone lines are usually busy [3]. Avaaj Otalo [41] proposed a voice forum for asking agriculture-related questions to experts and peers. It is an asynchronous system, meaning that responses are not given in real-time. Furthermore, questions can be answered by anyone, which may result in incorrect answers and distrust towards the system.

The above work suggests that to fully support the agriculture-related needs of farmers, constant, real-time access to specific information is needed. None of the systems in prior work achieve all of those criteria; FarmChat is an attempt to fulfill these requirements.

2.3 Conversational Systems

The last decade has seen rapid growth in conversational agents (also called *chatbots*). Chatbots have appeared on a variety of mobile and ubiquitous platforms, including phones, smart speakers, VR/AR devices, smartwatches and even operating systems (Siri by Apple and Cortana by Microsoft). The term 'Conversational Agent' has come to mean a wide variety of systems with varying capabilities and purposes, with the underlying assumption that human interactions with the systems resemble normal conversations. Proponents of chatbots embrace their many strengths: *e.g.*, user's familiarity with the conversational interaction, seamless natural-language interface across use-cases, offering direct information access and simplified navigational paths, and the promise of personalized and evolving intelligence [7, 32]. In spite of this rapid growth, chatbots are still in its nascent stage, as 84% of the Internet users have not used a chatbot yet [19].

From an HCI perspective, Licklider's 'Man-machine symbiosis' [31] was one of the earliest discourses that visualized humans interacting with machines in a natural manner. Although the HCI community has studied how conversational agents are used in different settings [22–24, 29, 30, 32, 44, 48], no prior work has focused on low literate users. The closest to our work is a study with first-time chatbot users [23], who were technologically-advanced literate Indians knowing about chatbots, but had not used them before. Most works evaluating users' experience with chatbots have discovered a gulf between experience and expectation with respect to the capabilities of chatbots [23, 30, 32, 48]. Users were found to be disappointed and even frustrated with the current bots [23, 32], and most chose to limit the usage of chatbots to simple tasks (*e.g.*, setting alarms) [32]. This suboptimal user experience can be attributed to the high expectations of expert users that these chatbot technologies currently target [23, 32]. In contrast, our work focuses on developing chatbots for low literate novice smartphone users who have little knowledge or preconception of the technology.

To summarize, speech-based conversational interface has several potential benefits for our targeted farmers population. Besides little requirement for literacy, it offers a natural and familiar modality that does not require a user to learn new technical concepts or interaction methods. This could be important as rural farmers often have low technology literacy and self-efficacy. Meanwhile, knowledge base of the conversational system can be easily edited or customized by agriculture experts, thus offering a scalable solution for disseminating information and expert advice. However, it still calls for empirical understanding for the acceptability and usability of this new type of technology among the farmers population. Our study set out to fill this gap.

3 FORMATIVE FINDINGS

Two sources of knowledge informed the development of FarmChat: farmers' information inquiries with the Kisan Call Center (KCC) and findings from a formative study with local farmers and agri-experts.

The Government of India has made all logs of calls to the KCC from January 2015 to September 2017 publicly available. In total, this corpus contains data for 8,012,856 calls. Each call log has 11 fields, including the date and time of the call, location, crop (one of the 306 crop types), query, and the answer provided by the KCC agri-expert.

For implementing FarmChat, our system was restricted to potatoes since most farmers around Ranchi were engaged in potato farming during the study period. Moreover, farmers are more keen to gain knowledge about the crop they are currently farming [15]. There were 85,852 calls related to potato crop in the KCC dataset. We performed topic modeling using LDA [6] on these calls and found that the top 5 queries for potato farming were pest and disease (52,070 queries), weather (11,628), best practices (5,648), fertilizer use (4,049), and seeds (3,646); these calls constituted 89.7% of the total potato farming calls. The majority of pest and disease queries (17,668) were about the late blight disease. FarmChat covers these main areas of questions with curated answers.

The KCC dataset does not contain the complete dialogues between the farmer and the KCC expert, but rather a limited summary of the question and the answer provided. To fill this gap and validate that the common questions identified from the KCC dataset apply to the local situations around Ranchi, we conducted semi-structured interviews with 14 farmers (9 male, 5 female) and 2 male agri-experts, in September 2017. We worked closely with a local agriculture NGO (Non Governmental Organization), where the two agri-experts were employed. They helped us recruit the farmers and obtain their consent for participation, following their own internal ethics policies. The farmers were from three different villages situated within 50 miles of Ranchi. Five farmers were *literate* (can speak, read and write Hindi), three were *semi-literate* (can speak and read Hindi), and six were *illiterate* (can only speak Hindi). The definition of different literacy levels have been adapted from previous works [13, 28]. Six of the literate and semi-literate farmers owned a smartphone with Internet access. Both agri-experts had a graduate degree in agriculture and more than 15 years of farming advisory experience. Though five of the farmers and both the agri-experts had heard about the KCC, only two of them have tried calling the service and none of their calls were answered. One of the researchers conducted the interviews. The interviews were conducted in Hindi and took 20 minutes. All sessions were audio-recorded, and were transcribed and translated to English later. Both the farmers and the agri-experts participated in the study voluntarily without compensation. From the interviews, we tried to understand: (1) What are the information needs of these farmers? (2) What are their current approaches to seek that information? (3) What are the concerns and limitations of these approaches?

These questions are intended to inform the potential usage patterns of FarmChat. We performed a thematic analysis [2] on the interviews data to identify themes related to the above three questions.

3.1 Information Needs

The farmers (denoted as *F*) and agri-experts (denoted as *AE*) provided us with similar questions as the ones we found in the KCC dataset. Based on both sources, we identified four major areas requiring information support:

Plant Protection: In the KCC dataset, 60.6% of the potato farming calls were related to remedies for protecting plants against pests and diseases. Similarly, agri-experts stated that a majority of farmers seek suggestions on which medicine to spray for a particular crop disease. None of the farmers we interviewed were aware of any disease name. Usually, farmers describe crop diseases by their visible symptoms to the agri-expert; with a few back-and-forth questions, the agri-expert hypothesizes the issue and recommends medicine with dosage information. This example conversation was provided by AE_1 – F: "*The leaves have big brown spots, what should I do?*", AE: "*How was the weather in the past few days?*", F: "*It has been foggy.*", AE: "(Must be the late blight disease.) *Spray Ridomil ...*". This is analogous to visiting a doctor with medical symptoms. In the design of FarmChat, we follow a similar Q&A conversational style.

Weather: In the KCC dataset, 39.4% of the overall calls were about weather-related questions; 13.5% of potato farming questions were about weather. Farmers eagerly sought weather information, as rains can wash away expensive sprayed pesticides and weather conditions determine the best time to harvest crops. A few commonly-asked questions by farmers were: "*Is it going to rain tomorrow?*"- F_3, "*Should I spray pesticide today?*"- F_8. The farmers we interviewed primarily relied on local regional television channels for weather information.

Best Practices: Information related to best practices can help increase yield in terms of the quantity or quality of potatoes. Common questions were: "*Till what height should I put water?*"- F_1, "*After how many days, should I harvest?*"- F_{12}. These best practices questions comprise of 6.6% of the potato farming calls in the KCC dataset. Agri-experts also stated that farmers consistently asked them tips to increase yield and, consequently, income. For instance, "*On harvest, I got small potatoes. What did I do wrong?*"- AE_2. Such a question would lead to a longer conversation, as the agri-expert lists different possibilities that might have resulted in small-sized potatoes, *e.g.*, seed size, fertilizer used, irrigation. FarmChat is designed to follow similar Q&A conversations.

Unbiased Recommendations on Products: Apart from best practice questions, farmers wanted recommendations from agri-experts on products they should purchase. Questions such as "*Which fertilizer to put and how many times?*"- F_3 and "*Which seeds are the best for red potatoes?*"- AE_2 were commonly asked. They prefer to ask these questions to agri-experts instead of local shopkeepers, believing that agri-experts would provide unbiased and trustworthy response; they feared that shopkeepers may be motivated by the profit margin of products.

3.2 Current Information Sources, Challenges and Design Requirements

With the formative study, we focused on understanding farmers' current sources to access farming related information and identifying their limitations, in order to inform design requirements for FarmChat. In Table 1, we summarize the main information sources and challenges in using them. Based on them, we identify the following design requirements and how we intend to address them in FarmChat.

Specificity: Farmers often request information on highly specific problems such as diagnosing issues of their crop, which is hard to satisfy by current automated information sources, including Google search and agri-apps. Farmers often have to turn to agri-experts but their availability is limited and it is difficult for AEs to address farmers' inquiries in a timely fashion. Chatbot enables more interactive search through multi-turn conversations [42]. We utilize that in FarmChat by asking follow-up questions to narrow down the information queries if needed. With the input from agri-experts, we attempted to follow their way of diagnostic discussions with farmers.

Localization: A main area of farmers' information needs focuses on local information such as weather and harvesting time. This again cannot be satisfied by most automated information sources or television. In designing FarmChat answers, we relied on local agri-experts to customize the information based on local conditions.

Trust: Trust is a theme that repeatedly appeared in the interviews. Most of the farmers were highly skeptical of the advice given by friends, shopkeepers, and agri-apps. Given the importance of agriculture information to the farmers' livelihood, it is critical and also challenging to build trust. The literature suggests that trust implies both competency and unbiased viewpoints [14], which we attempted to achieve through iterative development of the knowledge base with pilot studies, and acquiring contents from agri-experts of local NGOs. Whether farmers could trust the information provided by FarmChat is an open question that we look to answer in our study.

Persistence: While using most audio-based systems, such as automated agri-advisory, the KCC, agri-experts, *etc.*, due to low literacy, farmers cannot write down the recommendations given to them, resulting in repeated inquiries for the same information. The audio-based chatbot allows easy re-access of information. The Audio+Text version offers additional benefit of persistence, where the user can easily access previous messages.

Availability: Agri-experts and the KCC are not available throughout the day. Farmers also feel it is socially unacceptable to contact experts too frequently, however responses on WhatsApp cannot satisfy immediate information needs. Google search and agri-apps are thus favored by some farmers (4/14) to access information at any time. The chatbot solves the problem by allowing access at any time anywhere from one's mobile device.

Table 1. Current information sources and their challenges summarized in the square brackets.

Source	**Description**	**Count**	**Quotes and Challenges**
Self	Prior knowledge	14	"*Just do what I think is right*" - F_9; "*gut feeling*" - F_2.
Friends	Others with prior experience	7	"*Ask my friends who have previously seen the same disease*" - F_3; "*Because of jealousy, others give wrong advice. There is a lot of ill feeling... I never trust them.*" - F_{13} [Distrust].
Shopkeeper	Shopkeepers selling agricultural products	10	"*They just want money so sell their unsold stuff.*" - F_9; "*Sometimes he sell stuff which is not required. Only 1 medicine can solve it, but he will give 2 medicines.*" - F_{13} [Distrust].
Television	For daily weather updates	14	Not localized to their particular region [Localization].
Agri-Advisory	Receives automated calls 2-3 times a week with agri-tips from the Government	8	"*very generic... not relevant for my current problem*" - F_2; "*The advices are mostly for North Bihar which has more fertile land. Here we have rocky land, so all those advice fails.*" - F_7 [Specificity, Localization].
KCC, Agri-Expert	Call KCC or agri-experts, employed/trained by the local agri-NGO	11	"*They* (KCC) *don't pick the call, ever.*" - F_3; trust the responses from agri-experts but hesitate to bother them too often; advice received over the phone was hard for farmers to remember as they can not write down the responses due to illiteracy [Availability, Persistence].
WhatsApp with Agri-Experts	Hesitant to interrupt agri-experts, so message them on WhatsApp with images of the diseased crop	5	"*delayed responses*" - F_2; "*It does not work. For the image of infected crop, we need to ask a few follow-up questions... Whatsapp is like a 1-way communication channel with high lag... as they are illiterate.*" - AE_1 [Availability].
Google, Apps	Farmers with smartphones search on Google or agri-apps (such as MyAgriGuru, Gramophone)	6	"*You ask one thing* (to Google) *and get thousand responses. What to do*!" - F_{11}; "*With Google, I do not trust the response.*" - F_3; "*the apps are developed by big agricultural corporates... to advertise their own products*" - F_8 [Trust, Specificity].

In summary, we designed the proposed novel chatbot solution, FarmChat, to respond in real-time, be available 24x7, provide specific responses to custom queries in the local language, and give localized answers provided by the local agri-experts ensuring the information content received by farmers to be unbiased and trustworthy.

4 FARMCHAT SYSTEM DESIGN

In this section, we will describe the developed FarmChat system (Figure 1). We will start with providing the system's overview, followed by describing its three major components: the two versions of the user interface (Audio-only and Audio+Text), the generated knowledge base derived from the KCC dataset and inputs from agri-experts, and the conversational intelligence combining intents, entities, and dialogue.

4.1 System Overview

To interact with the FarmChat mobile app, the user clicks the red microphone button and speaks after hearing a 'beep'. Once the app detects a long silence, it stops listening. After every user speech input, the screen displays a waiting icon to acknowledge that the system has begun to process the user's input and is retrieving a response. In the current version, FarmChat supports Hindi. We chose Hindi because 41.1% of Indians are native speakers of Hindi [17], and all the farmers in our study region know Hindi. The phone app passes the received speech

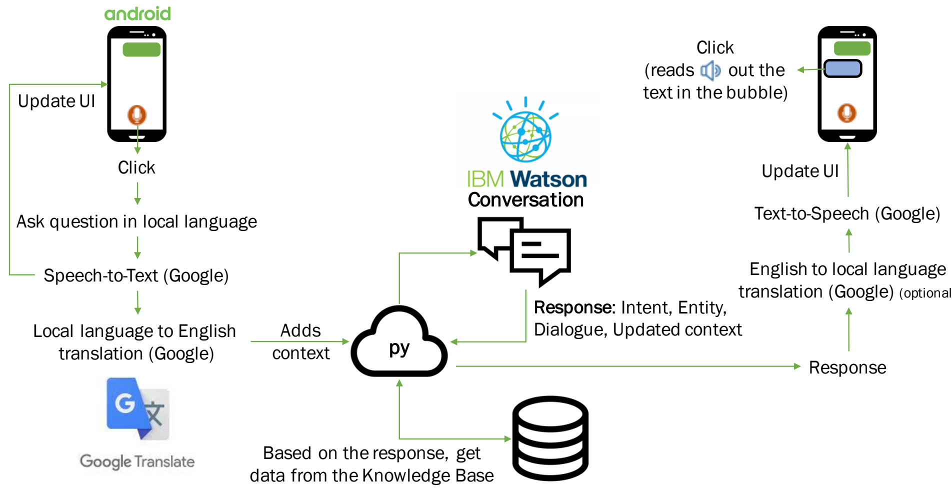

Fig. 1. System Design of FarmChat

input through Google's Speech-to-Text transcription service (Hindi speech to Hindi text) and then through Google's language translation service to translate the Hindi text to English (Figure 1). The translated English text, along with the current context of the conversation, is then passed to a back-end application built with Python Flask. The Python application passes the English transcription and context to IBM's Watson Conversation service, which identifies the intent and entity in the text based on a pre-defined language model. The IBM Watson responds with an updated context and response in English text, based on a pre-defined dialogue flow. The details of the dialogue flow will be discussed in Section 4.4. The response from IBM Watson is received by the Python application and may consist of a few empty fields. Those empty fields are populated by retrieving data from the domain-specific knowledge base database. For example, when a user asks "*can see black spots on the leaves, what to do?*", the IBM Watson understands that the user needs information related to the 'cure' of 'late blight disease' for 'potato'. Information for the cure is then retrieved from the knowledge base. Separating the dialogue flow logic and knowledge base allows agri-experts to make easy edits to the knowledge base without impacting the conversation model. The final response text with updated context is sent to the FarmChat phone app. If the received response is in English, the system translates the response to Hindi using the Google translation service. FarmChat then reads the text to the user, using Google Text-to-Speech, thus completing the conversation.

4.2 User Interface

Most rural farmers in India are illiterate or semi-literate [28]. Recent work suggests supporting semi-literate users differently in interface design from illiterate users [13]. The appearance of text might negatively impact the illiterate users [34], while text for semi-literate users offer faster and unambiguous mode of interaction [13]. More importantly, the additional modality of text-based output allows persistent access to previous messages, which is identified to be our key design requirement. In this work, we examine two variants of FarmChat: Audio-only (input: speech; output: audio) and Audio+Text (input: speech, button; output: audio, text, image).

4.2.1 Audio-only FarmChat. The Audio-only FarmChat interface (Figure 2) consists of only two buttons: (1) a red 'microphone' button that the user needs to click to provide speech input, and (2) a blue 'play' button, which enables the user to listen to the chatbot's last response again. Users can click on the blue button any number

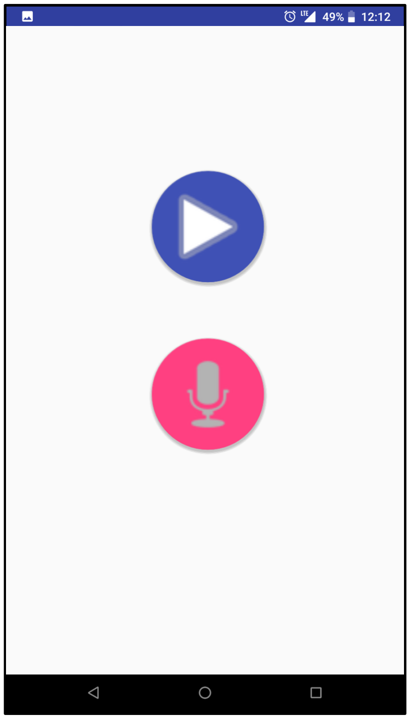

Fig. 2. User Interface of Audio-only FarmChat

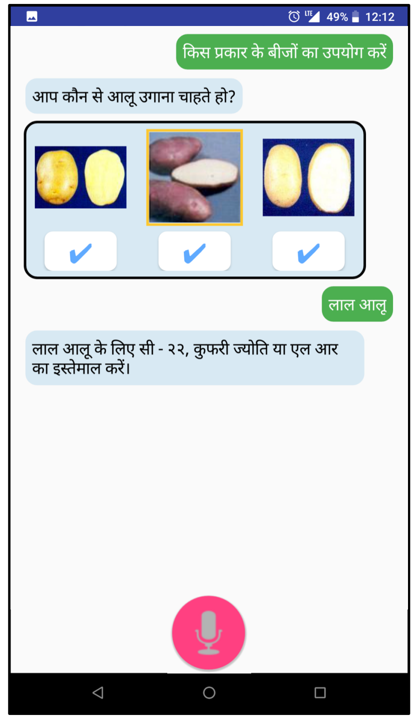

Fig. 3. User Interface of Audio+Text FarmChat

of times to repeat the most recent response. While the bot is playing the last response, the blue button can be clicked again to pause the response. After the user's speech input is received, the interface shows a waiting icon and does not allow the user to click any of the buttons. This was done based on the results from a pilot study with 4 farmers that uncovered major design issues. We found participants had a tendency to talk further while waiting for the bot's response, perhaps presuming that the bot did not understand the previous input. Once the Audio-only FarmChat app receives the bot's response, it removes the waiting icon, and speaks out the response.

4.2.2 Audio+Text FarmChat. The Audio+Text FarmChat user interface (Figure 3) closely resembles a typical text-messaging interface, wherein the user input and bot response are presented in message bubbles. There are two major differences from a typical text-messaging interface: (1) Audio+Text FarmChat can only receive speech and button click input, not text; (2) The text/image output can be processed as audio, *i.e.*, clicking on a message bubble in Audio+Text FarmChat results in it being read aloud through Text-to-Speech.

Similar to Audio-only FarmChat, the user needs to click the red microphone button and then speak in order to provide speech input. Using Speech-to-Text, the system converts the Hindi speech input into Hindi text, which appears in a new green-colored bubble (aligned right) on the messaging interface. The response text from the bot appears in a new blue-colored bubble (aligned left) on the interface, and it is read aloud using the Text-to-Speech service. If multiple bubbles get added in the same response, they are read aloud in order. Users can scroll up to access previous messages; tapping any message bubble reads it aloud to the user. The message bubble currently being read gets highlighted with a black border around it. The user can pause the audio play by tapping the same bubble again. The audio automatically pauses when the user presses the microphone button to provide new input.

Audio+Text FarmChat use images in two ways – for asking multiple choice question, and for explaining a farming concept. As shown in Figure 3, for example, the user asks FarmChat '*what kind of seeds should I use*', to which the bot responds, '*which potatoes do you want to grow?*' with three images as options '*white potato*', '*red potato*', and '*potato for chips*'. The user can either press the microphone button and say the response to the question aloud or click one of the three tick-mark buttons to select a particular option. The user can also click the image to hear a description of the selected image. The response from the bot may also contain images to explain certain concepts. For example, regarding the question '*how much water is ideal for irrigation?*', the bot responds with an image explaining that '*give water up to two-thirds of the ridge's height*'.

4.3 Knowledge Base

We developed a knowledge base for potato farming using the KCC dataset and information collected from formative interviews with farmers and agri-experts. For each of the identified topics in Section 3.1, we asked the two agri-experts (who participated in the Formative Study) to provide examples of typical farmer questions, the follow-up questions that they would ask in order to understand the problem, and the final advice they would provide. All such conversations was added to the IBM Watson Conversation dialogue flow, and the informational advice was included in the FarmChat knowledge base. In the current version, the knowledge base is a SQL database consisting of four tables, one for each of the topics identified in Section 3.1. Each table has a crop type, multiple tags, and the knowledge from agri-experts, *e.g.*, one of the rows in the Recommendation table has '*potato*' as crop type, '*seeds*' and '*red*' as tags, and '*C-22, Kufri Jyothi, and LR*' as the recommendation associated with the combination of these tags and crop type. The knowledge base can be easily extended to add more crops and/or more data related to each crop.

The knowledge base was iteratively populated. During the pilot study, we learned that a few standard Hindi words are not well understood by the local farmers. For instance, given the instruction "*for irrigation, give water up to two-thirds of the ridge's height*", many farmers did not understand the phrase "two-thirds". We modified the knowledge base using local terms with the agri-experts help, adding examples to make it easier for the farmers to understand. In the above example, for instance, we added "*... for 6 feet ridge's height, fill it till 4 feet of water.*"

4.4 Conversational Intelligence: Intent, Entity and Dialogue

During our formative interviews with farmers and agri-experts, we learned that the farmers are often not familiar with disease names and are most likely to describe the visual symptoms. Supporting such interactions requires developing a robust conversational back-end.

Conversation systems identify *intents* and *entities* from user's input to understand the meaning of the user text. The user's *intent* is the current goal or purpose of their interaction with the chatbot. The *entities* add value to that purpose and narrow it further to make it specific. For any chatbot, the intent and entity types are defined by the chatbot designer. As the conversation involves multiple back-and-forth rounds between the user and the chatbot, the conversation system maintains *context* to keep track of the discussion. The context comprises of a selection of intents and entities from previous utterances. Without context, a user's new input would be processed oblivious of their previous inputs. Based on the intent, entity and context, the response is generated as per the *Dialogue flow* detailed by the chatbot designer. As an example, here is a typical conversation with FarmChat:

> Human: *can see black spots on the leaves, what to do?*
> Bot: *tell me how was the weather for the last 5 days?*
> Human: *mostly rainy*
> Bot: *spray Ridomil ...*

From the first message by the user, FarmChat recognizes that the intent is '*plant protection*', with the entity being '*black*' spots. Black spots can be a symptom for several diseases. To accurately diagnose the problem, FarmChat asks a follow-up question taken from the Dialogue flow. As the conversation proceeds, the chatbot maintains the context of plant protection so that the '*rainy*' intent corroborates with black spots to identify '*late blight*' as the disease. Overall, we defined 38 intents, 12 entities, and the dialogue flow in the IBM Watson Conversation.

5 FARMCHAT COMPARATIVE EVALUATION

We conducted a user study (in February 2018) to understand the usability of the FarmChat system.

5.1 Participants

Thirty-four farmers (15 female, 19 male) with average age of 40.5±14.3 years and farming experience of 17.9±11.5 years participated in the study. They were from six different villages situated within 50-100 miles of Ranchi, India. A local NGO staff helped to recruit the participants. The NGO staff also obtained consent of the farmers for participation, using their own internal ethics policies. The NGO actively collaborated with the researchers on this project; neither the NGO nor its staff received any funds from us.

All participants spoke Hindi and Khortha, the local language. Eleven of the participants were illiterate, nine were semi-literate and fourteen were literate (Table 2). Thirteen participants owned a touch-screen smartphone. Only one of them used the smartphone just to receive incoming calls. The remaining 12 participants were typical smartphone users, using the phone for browsing Internet, watching videos, and extensive WhatsApp usage. We consider these participants to be *digitally-literate*. Among the 22 digitally-illiterate participants, one owned a smartphone and twelve had access to a smartphone at home with their son or husband, but they only used it to receive incoming calls. Nine out of the 12 digitally-literate participants were agri-entrepreneurs (Table 2). *Agri-entrepreneurs* are farmers who have undergone a 35-day agriculture-related training program conducted by the local NGO. As part of the training, each agri-entrepreneur receives a Samsung smartphone (costing 60 USD). Overall, nine participants knew about the KCC. Of those participants, only two had called the KCC, and only one had received a response once. None of the participants had any prior experience with a chatbot. Participation was voluntary without financial compensation.

5.2 Procedure

We conducted a task-based user study to compare the two interfaces using a within-subject design. The ordering of the interfaces was randomized across participants to counter ordering effects. Before the tasks, participants went through a training task to learn how to use each interface. The training comprised of three dialogues: (1) Exchanging greetings: FarmChat asks the participant "*how are you?*" and waits for the participant to respond. (2) Gender information: FarmChat asks about the participant's gender. For Audio+Text, it shows multiple choice image-based options. (3) Family size: FarmChat asks the participant the number of people in his/her family and expects a number in response. The training was the same and required for both interfaces. To help participants remember the primary mode of interaction, they were told: "*to listen, press blue; to speak, press red*".

After completing the training successfully, participants were asked to perform three tasks: a structured task, a semi-structured task, and an unstructured task (in that order). The structured task was used in the beginning to help familiarize participants with the interface. For the structured task, participants were shown paper-printed color images of symptoms related to four common potato pests/diseases. Participants were asked if they have seen any of these pests/diseases in their own field or in their neighbor's recently. If yes, the participants could ask FarmChat questions about it. This was done to ensure that the participants were able to answer follow-up questions by FarmChat about the particular pest/disease. Each question related to pests/diseases requires at least three dialogue exchanges in order to ascertain the remedy. For the semi-structured task, participants were shown paper-printed color images of four major farming practices: buying input seeds, seeding, irrigation, and harvesting (including bad yield). Participants were required to ask at least one question related to farming practices to

FarmChat. Finally, for the unstructured task, participants were encouraged to ask any potato farming-related questions on their mind. This task was aimed to help us identify the knowledge gap within FarmChat. Throughout all of the tasks, one of the researchers helped participants when needed, to ensure that all tasks were completed.

Apart from these tasks, demographic information was collected at the beginning of the study. After completing all the tasks with a particular interface, participants were asked to rate their usage experience by answering eights questions on a five-point Likert scale – enjoyment in using the system, ease of use, difficulty in learning, support they would need in the future to use it, satisfaction in the input interpretation, trust in the response, speed, and willingness to use it in the future. Note: Except the questions regarding difficulty in learning and future support, higher scores indicated a better experience. These questions were followed by a semi-structured interview, which delved deeper into specific features that participants liked or disliked with suggestions for improvement. At the end, participants were asked about their preference between the two interfaces.

During our pilot study with 4 participants from the same demographic, we encountered several errors with the Speech-to-Text and language translation services. Hence we decided to complement these services with a wizard-of-oz approach. Specifically, one of the researchers acted as a wizard, and updated the participants' transcribed and translated text minimally to correct any errors from the Speech-to-Text and language translation services before passing those messages to the Python-based back-end application. It is important to note that the wizard did not interfere with the conversational back-end (*e.g.,* intent classification). This is in contrast to a complete wizard-of-oz system where the wizard is a proxy for an automated conversational system (*e.g.* [44]).

The two researchers – one conducting the study and another acting as wizard – were accompanied by a local NGO staff member during the study. All interactions between the researchers and participants were in Hindi. All sessions were audio-recorded, and were later transcribed and translated to English. Participants' interactions on the phone and the wizard's interactions on the computer were logged. The study took place in the participants' home or farm land. On average, each participant took 60 minutes.

5.3 Hardware

All the participants performed the tasks on a Lenovo K8 Plus phone (screen: 5.2 inch, price: 150 USD). The current FarmChat system requires access to Internet, and the Internet data requirements were ideally fulfilled by a 4G SIM card on the phone. Moreover, the wizard's MacBook Air laptop also used the phone's Internet using hot-spot.

6 RESULTS

In total, participants (denoted as *P*) provided 626 inputs to FarmChat. Inputs entail only speech in Audio-only FarmChat, and both speech and button clicks in Audio+Text FarmChat. Inputs can be in the form of questions, answers, or comments. General statistics are summarized in Table 3. We conducted paired t-tests between the two interfaces on various parameters, and did not find any significant difference between the two interfaces. Figure 4 shows the Likert scale ratings for FarmChat. To compute this, we used the ratings given to the FarmChat interface that was *preferred* by the particular participant.

For evaluating the FarmChat system and understanding the opportunities and challenges of using conversational systems for rural Indian farmers, we focus on three main aspects: (1) the acceptability of FarmChat as an information system to satisfy farmers' information needs, (2) the usability in interacting with conversational interfaces, and (3) the preference between the two variants of conversational interfaces – Audio+Text versus Audio-only – and how it differs for different user populations (literate versus semi-literate versus illiterate users, digitally-illiterate versus digitally-literate users, farmers vs agri-entrepreneurs). To explore these, we rely on demographic information, log data, Likert-scale ratings, user study notes by the study facilitator, and audio transcriptions of the user study and post-study interviews. Two authors individually reviewed the audio

Table 2. Demographic data for the user study (refer Section 5.1). Note: The same 34 participants are categorized with respect to their literacy level, smartphone usage and profession. (A-o: Audio-only; A+T: Audio+Text; I: Illiterate; SL: Semi-literate; L: Literate; m=mean; std: standard deviation)

LITERACY	**Illiterate**	**Semi-literate**	**Literate**
# of participants	11	9	14
Gender (M,F)	3,8	7,2	9,5
Age (m±std)	43.9±15.9	43.1±16.2	36.1±11.2
Years in school (m±std)	1.3±1.3	5.6±1.7	10.3±3.0
Digitally-literate	0	1	11
Agri-entrepreneur	0	0	9
Preference (A-o,A+T)	11,0	5,4	2,12
SMARTPHONE	**No**	**Access**	**Owns**
# of participants	9	12	13
Gender (M,F)	6,3	5,7	8,5
Age (m±std)	45.5±16.4	41.8±15.2	35.8±11.2
Years in school (m±std)	2.7±3.0	4.3±5.1	9.2±3.9
Literacy (I,SL,L)	4,5,0	6,3,3	1,1,11
Agri-entrepreneur	0	0	9
Preference (A-o,A+T)	9,0	6,6	3,10
PROFESSION	**Only farmer**	**Agri-entrepreneur**	
# of participants	25	9	
Gender (M,F)	13,12	6,3	
Age (m±std)	42.4±14.7	35.3±12.3	
Years in school (m±std)	4.2±4.5	10.1±3.4	
Literacy (I,SL,L)	11,9,5	0,0,9	
Digitally-literate	3	9	
Preference (A-o,A+T)	18,7	0,9	

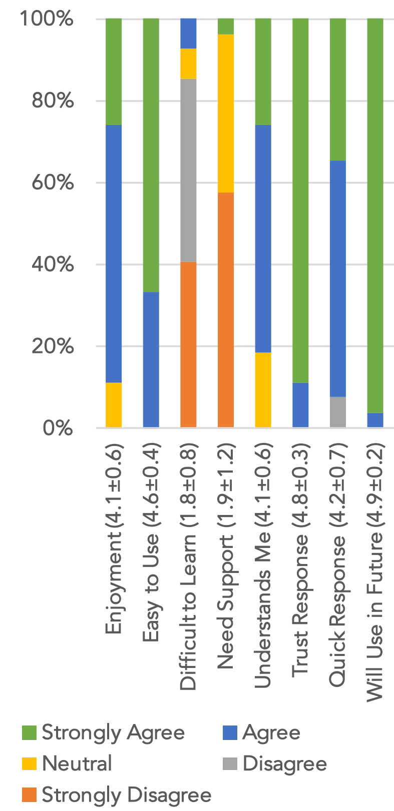

Fig. 4. Likert-scale rating considering ratings for the interface preferred by the participant

transcriptions and used open coding to extract themes [2]. Codes were harmonized after two iterations of review and discussion, resulting in the final set of themes in each of the above mentioned aspects.

6.1 Information Acceptability

Overall, we found FarmChat to be generally acceptable by the farmers as an information source to satisfy their farming information needs. All participants expressed willingness to continue using FarmChat in the future (Figure 4). The major reasons that farmers enjoyed using FarmChat were immediate responses to their queries and constant access to farming-related knowledge. For example: "*Information is the key... If I know more, I will earn more!*" - P_{10}, "*It gave me new knowledge... like treating the seed initially will help... It even told me medicines.*" - P_{16}. In particular, responses that included a medicine name and quantity were re-read and replayed most often (2.4±1.5 times for Audio-only). This may be because they wanted to memorize the names or the hard medicine names were not clear to them in the first attempt. Four participants even asked for FarmChat to be installed on their personal device: "*Give me this on my phone. I will use it. I will learn from it, and even teach others.*" - P_{12}. A few participants (3/34) also discussed the potential value of having continuous access to FarmChat beyond in-situ information needs: "*when I am free, I can ask for which fertilizer to use, how much... I can gain new knowledge.*" - P_{26}. This suggests that compared to existing human information sources like the KCC and agri-experts, a chatbot

Fig. 5. FarmChat speech-based interaction

Table 3. Results from log data, mean±std. No significant difference was obtained between the two FarmChat interfaces.
(*Cannot be calculated accurately, as a majority of literate participants read the response multiple times instead of tapping the chat bubble. The reported number is for the sake of completeness.)

Data Type	Audio-only	Audio+Text
Time spent/participant (mins)	14.8±8.5	12.7±6.6
Total # of speech, button click input	275, –	304, 47
# of speech input/participant	8.1±2.2	9.2±4.5
# of button click input/participant	–	1.4±1.1
Length of speech input (words)	6.1±4.8	6.8±4.5
Length of speech input (sec)	7.1±1.3	7.4±1.6
% of bot's response replayed	51.7±32.2	46.8±33.1*
% mic button clicked but no input	15.4±14.1	18.5±13.0

system has the potential to better serve farmers' needs for continuous learning. In the following, we summarize themes that emerged from the user study on information assistance provided by FarmChat.

Precise and Localized Answers: Specificity and localization were identified as keys to the information needs of farmers. With the help of agri-experts, we carefully tailored the system responses to local conditions. Participants appreciated such information contents: "*Gave precise answers for the disease related questions*" - P_{15}, "*I know that these medicines are available locally.*" - P_4. However, needs for even more fine-grained localization and personalization still emerged. *E.g.*, P_4, who praised the localized responses complained "*the big seeds it is advising is not available here*". Also, "*my land is rocky, the soil is not sandy. Hence for harvesting it requires adding water... she is suggesting to stop water a week before harvesting, which may work well for other's field, not mine.*" - P_4.

Trust: Trust is another key design requirement. In general, participants trusted the responses provided by FarmChat (Figure 4). Six participants even asked the facilitator to write down the recommended medicines, seeds variety, and/or fertilizer with their quantities for them to refer later. Participants often formed trust in FarmChat by validating its responses with their existing knowledge. For example, "*I used the Bevestin medicine for wheat, and I was really happy with the results. This phone* (app) *is telling me to use Bevestin for potato, so must be telling the right thing.*" - P_{10}, "*Its giving all correct information... some NGO people... a while ago, gave us similar information.*" - P_3. The researchers were accompanied by a local NGO staff during the study. This assumed endorsement might have also made the FarmChat more trustworthy for the rural farmers, as observed before in prior work [8, 9].

Over-expectation: We found participants' tendency to overestimate the capabilities of FarmChat, which led to some level of dissatisfaction in usage. Lack of clear affordability is a known challenge for conversational interface [32], but the novelty effect for the farmer population seemed to exacerbate the problem. Although FarmChat had high success rate (overall only 21 out of 238 questions went unanswered), some participants (4/34) were still disappointed when one of their questions was not answered and said: "*Why are you making excuses?*" - P_{25}, "*it should have the answer to all questions*" - P_{24}. Moreover, many farmers (15/34) got excited, and in spite of being told it could only help with potato-farming related queries, they started asking questions about other crops (*e.g.*, onions, tomatoes). In particular, farmers wanted to learn about "new" crops like lettuce and broccoli because no one in their village had grown them before.

6.2 Chatbot Usability

Although it was the first time for all participants to interact with a chatbot, they generally found the system to be usable, with the Likert ratings on usability being 4.6±0.4 and difficulty of learning being 1.8±0.8. From the user study, the following themes emerged as highlights of the usability and related issues of FarmChat.

Anthropomorphism and Familiar Phone Interaction: FarmChat by design was not anthropomorphic, as we did not introduce any human-like features such as name or character. In spite of that, we found our participants to have a high tendency to anthropomorphize the bot. A few participants (6/34) referred to the bot as "*didi*", which means elder sister in the local language, since the bot had a female voice. Some participants (4/34) said: "*ok*", "*good*", "*yes*", after every sentence said by the bot, as if they were talking to a human. Also, participants were very polite in their interactions. Questions usually began with "*please listen ...*", "*can you please tell me ...*", and ended the conversation with "*thank you for the help*", as if talking to an agri-expert. Only P_{32} explicitly treated FarmChat as a machine, and commented: "*Why should I respond to its good morning. Can I just ask my question?*". Also contrary to previous research with technologically-advanced users [23, 30, 32], farmers seemed to be "nicer" – more patient and more forgiving – to the chatbot. Participants even tried to frame their questions in formal Hindi, assuming it could help FarmChat understand them better. At times, the participant knew a particular term only in the local Khortha language, hence he/she asked the facilitator: "*What should I say* (for) *this in Hindi?*" - P_{29}. Our participants were trying to help the bot to understand their queries precisely. This is in sharp contrast to previous work [23], in which participants tried to 'break' or challenge the bot.

One reason our users anthropomorphized the agent could be that they resorted to their familiar mode of interaction in making a phone call. The farmers had no concept of a chatbot; hence, they interacted with it as if they were interacting with a human. This familiarity enabled participants to quickly grasp the interactions, as suggested by the ratings for difficulty of learning and support needed to use FarmChat in the future (Figure 4). However, mismatches between making phone calls and interacting with a bot posed some challenges. For instance, the participants would start responding to FarmChat's query as soon as it ends, without pressing the red button. They assumed that FarmChat was always listening, similar to a person on the other side of the phone line. Instead of increasing the phone's speaker sound, P_{17} said "*I can't listen properly, speak loudly*", assuming it was a human.

Speech as Input: Participants were pleasantly surprised that FarmChat was able to understand their complex questions in Hindi (rating 4.1±0.6). "*The question I am asking, it is able to understand well. Most times, only after a single attempt.* "- P_{26}. Note that this was partly due to the wizard's role in fixing errors in speech processing; 36.3% speech inputs were fixed by the wizard, as computed from the wizard log files. Speech as input failed for a few of the illiterate participants (4/11) who were not able to speak Hindi fluently. As they have never attended school, they learned Hindi from their neighbors, friends, *etc.* Their spoken Hindi was not grammatically complete and was strongly influenced by the local Khortha language. "*My Hindi won't be understood by the bot, as its mostly Khortha.*" - P_{29}. For such participants, the wizard edited 72.7% of the speech input.

Even when other interaction modalities were available, we found that participants still preferred to rely on speech input. For example, when buttons were available to provide precise input in Audio+Text, participants used speech 28.2±39.7% of the time to provide input instead of clicking the button. Moreover, instead of clicking the text-box (Audio+Text) or the replay button (Audio-only), participants occasionally asked FarmChat to "*repeat what you said*" - P_8. One potential explanation is that switching between touch and speech input was cumbersome.

Responses by Speech: A majority of the participants (18/34) appreciated the fast responses given by the bot in speech: "*very quick response, no wait*" - P_{26}. The average response time was 9.2±2.8 sec, which includes Google transcription and translation time (0.9±0.2), wizard time (5.7±4.5 during edits, 2.1±1.2 without any edit), Watson Conversation service with Python Flask response time (3.1±1.1), and network delays. Using button clicks for input significantly lowered the response time to 1.7±1.0 sec since neither the wizard nor transcription/translation services were used. Participants were generally satisfied with FarmChat's response time (Figure 4). Echoing the finding on persistence from our formative study, another highly appreciated feature was the capability to replay speech output, as participants at times had trouble understanding or memorizing the bot's responses– "*if I missed hearing something... I can easily play it again*" - P_{23}. Users clicked the bubble/button for replay frequently.

Interaction Order as a Usability Challenge: For a majority of illiterate and digitally-illiterate participants, the ordering of pressing the red microphone button, waiting for the beep sound, and then speaking was challenging to follow. Note that this order is required by the current speech input technologies. Many times, participants did not press the microphone button at all or started speaking before the beep sound. At times, the mic button was pressed but no speech input was received (Audio+Text: 18.5±13.0%, Audio-only: 15.4±14.1%). This often happened when the participants were thinking of what to say next, but the app stopped listening after it detected a long silence. Moreover, the interaction convention in Audio+Text interface was challenging for those who were unfamiliar with messaging interface. For example, such users were confused whether to scroll up or down to see the previous chat bubbles and had trouble understanding the addition of new chat bubbles. This again highlights the challenge of designing for population, which has limited experience with technology.

6.3 Interface Preference

We compared user responses to Audio-only and Audio+Text FarmChat interfaces. Our results suggest that users' preferences were highly dependent on the participants' literacy level, digital-literacy level, and other individual factors like profession, physical and environmental factors.

6.3.1 Literacy Level. All the illiterate participants preferred the Audio-only interface. Among the literate and semi-literate participants, 16 participants preferred Audio+Text, while others preferred Audio-only (Table 2).

Reading vs Listening: Literate and semi-literate farmers preferred Audio+Text for several benefits of text. First, the Audio+Text FarmChat enabled them to quickly access relevant information in the bot's response, such as medicine names and quantities; in the Audio-only interface, users had to listen to the whole response again. Second, participants found it easier to memorize "*crucial*" information (*e.g.*, seed name, fertilizer quantity) after reading it, compared to information that was only heard: "*can not remember just by listening*" - P_{26}. This has been supported by prior human memory research [4]. Third, reading allowed the participants to take in information at their own pace. "*Listening is easier, but she speaks very fast. I can read slowly in the first one* (Audio+Text)" - P_{32}. Fourth, the facilitator noticed that three participants took pride in the fact that they could read, with one saying "*it* (Audio-only) *is for illiterate people to use... I can read easily!*" - P_{32}. This is also supported by the behavioral data, as (semi-)literate participants chose to listen again much less frequently compared to illiterate participants (0.7±0.3 versus 2.2±0.7 times). This finding echoes a previous study, showing that a few participants (3/11) preferred the textual interface even though they could not read, to avoid the stigmatized perception of illiteracy [26]. However, seven of the (semi-)literate participants preferred Audio-only FarmChat because they found it to be less mentally demanding ("*nothing to read, so no tension.*" - P_{10}), they had limited reading skills ("*I can't read fast enough*" - P_{14}), and/or other environmental and physical reasons (discussed in Section 6.3.3).

Persistent Presence of Messages in Audio+Text: A key advantage of the Audio+Text interface is that previous conversations are persistently shown on the interface and can be accessed later by scrolling up to the message. This was appreciated by the semi-literate participants. "*I will not remember the medicine names, its quantity. In this* (Audio+Text)*, I can open again, whenever needed, and find the details.*" - P_6. On the other hand, persistently showing all information has its disadvantages – "*There is so much competition among farmers. If it is on my phone, other farmers may also read and learn. With the other one* (Audio-only)*, I will only listen.*" – P_{10}.

Complexity of Audio+Text: The researchers noticed that most illiterate participants struggled with the Audio+Text interface, but learned to use the Audio-only interface easily. First, illiterate participants found the Audio-only interface to be less complex, and easy to learn and use: "*Two buttons is easy. No tension... no confusion.*"

- P_9, "*less things to put my mind on*" - P_{21}. Second, illiterate users were scared and nervous when confronted with lots of written text, which reduced their confidence level. "*I can't do this.. its too hard. I won't be able to do it.*" - P_{34}. Third, as they could not read any of the text in the speech bubble, they easily lost their current context of interaction and were unsure of which speech bubble to click next. "*Touching in this* (Audio+Text) *is confusing as* (there were) *multiple things to touch, which to touch when... It is hard to remember which bubbles I have already heard, and which I have not heard.*" - P_{11}.

Numerically Illiterate: The researchers learned that a majority of literate and semi-literate users (11/23) were not able to read Hindi numerals. This is in contrast to previous findings that most illiterate people in India are numerically-literate [34]. One of the main reasons for the disparity is that English numerals are more prevalent in India than Hindi numerals. In FarmChat, numbers are crucial for specifying quantities like medicine dosages.

Usefulness of Images: The Audio+Text interface uses images both as part of bot's questions and to support certain answers. Images in the button click input was appreciated because it allowed participants to visually understand the multiple options. However, participants sometimes tried clicking the image itself for selection rather than the buttons, leading to confusion; similar findings were found in previous work [22]. The images in bot's response not only helped the participants better understand the responses, but also allowed them to locate previous threads. Illiterate users highly appreciated images of the medicine package, as they are often concerned about being sold the wrong medicines by the shopkeepers.

6.3.2 Digital-Literacy Level: Twelve participants were digitally-literate (Table 2). Twelve other participants had occasional access to a smartphone at home and were nervous to participate in a study involving one: "*My son doesn't let me use his phone as he thinks I might break it. He tells me just to click green button to* (pick the call and) *talk.*" - P_3. Self-efficacy, both in general and regarding technology specifically, impacted attitude and usage patterns. A majority of the digitally-illiterate users (16/22) preferred Audio-only interface.

Only two buttons and No scrolling: Since the Audio-only interface has only two buttons, it was "*easy to learn and use*" – P_3 by digitally-illiterate users. The Audio+Text interface was complex and confusing for them, since each speech bubble was a button. Moreover, due to limited phone screen size, the buttons in the Audio+Text interface were comparatively smaller than that of the Audio-only interface, which made them more likely to miss buttons. Finally, scrolling was not intuitive. The log data shows that none of the digitally-illiterate users scrolled even once in the Audio+Text interface, while participants using smartphone regularly scrolled 4.5±2.4 times.

6.3.3 Other Individual Factors. We also found the following factors affected the interface preference:

Environmental and Physical: A few participants (6/34) determined their interface preferences based on environmental or physical factors. Semi-literate P_7 chose Audio-only because "*in the field, in sunlight, I can not read* (text on the smartphone display)", while P_{18} preferred Audio+Text because he was not able to hear properly due to the noise from a nearby tractor. P_{14} liked Audio+Text because he has hearing problems, while P_3 and P_{17} chose Audio-only because they had eyesight problems. One of the older participants (P_{28}) preferred the Audio-only interface because he had shaky hands that prevented him from pressing smaller buttons.

Profession: All our participants were farmers. Nine of them were also agri-entrepreneurs, along with being farmers. All agri-entrepreneurs recommended Audio-only for the farmers in their village, but preferred Audio+Text FarmChat for their personal use in helping others. "*After listening, I might not remember everything. With written stuff* (in Audio+Text)*, I can quickly look it up... only the relevant part and tell others... rather than listening to the whole thing again* (in Audio-only). *Also, it will certainly reduce my chances of making errors.*" - P_{27}, "*I don't want to listen in front of others and advise them.*" - P_{26}. This point is interesting as they considered the interaction modality as part of their self-representation; they did not want to be seen as taking help from their phone. In contrast, agri-entrepreneurs thought Audio-only would suit the other farmers better as they tend to have low literacy and low digital-literacy level. "*Most people here are illiterate*" - P_{24}, "*I can easily give this* (Audio-only) *to others, and provide training on how to use on their own. With just two buttons, they can easily use it.*" - P_{12}.

7 DISCUSSION

In this paper, we propose the use of a conversational agent, implemented using cloud-based scalable services, as a way to help address the information needs of rural farmers. From the user study, we found positive evidence for introducing chatbot technology as a usable solution for serving the information needs of Indian farmers. With FarmChat, it was possible to provide satisfying answers for common questions that farmers encounter in their farming activities. With the help of local NGOs to edit and endorse content, farmers showed trust in the information given by FarmChat. As expected, a speech-based conversational interface cater to the low-literate and digitally-illiterate users, as the resemblance with human-human interactions made it easy to use and required little learning. We discuss a few key points as design implications below.

7.1 Design Implications

Future Conversational Interface: The study results suggest that the two versions of interfaces–Audio-only and Audio+Text–each have their own advantages, and user preferences depend on several individual factors. Therefore, we suggest a hybrid interface that incorporates positive features from both variants. The hybrid interface would show two buttons, like the Audio-only interface preferred by illiterate and/or digitally-illiterate users. An extra button would allow users to toggle the view and provide a conversation history in the bubble chat format, adopting from the Audio+Text interface favored by semi-literate and literate users. To complement the current limitations in processing speech input, the image-based multiple-choice mechanism to provide precise input can be shown below the two buttons in the hybrid interface when appropriate. It can also show images in the output below the two buttons to aid users in understanding the bot's responses.

We also suggest the following improvements for interface elements: (a) instead of the red microphone button, a green-colored call button can be used as users related FarmChat directly to making phone calls, (b) domain-specific terms such as medicine names are less familiar to farmers but critical to their work. This results in farmers often reading and listening to such responses multiple times. In the future, the app should emphasize these special terms by highlighting them and/or repeating them in speech. Finally, as we found participants struggling with Hindi numbers, a hybrid language with the numbers in English should be used.

Speech as Input: First-time smartphone users struggled with providing speech as input. One major issue was that the period of detecting silence was short; while participants paused to think, FarmChat stopped listening, which was frustrating for the participants. There are several solutions to this. FarmChat could listen for longer *initially* by extending the expected silence time at first and decreasing it over time. Based on the average length of speech input, we suggest 7-8 seconds would be optimal. Alternatively, the chatbot could remind users to press a button to reply, highlight the button after the bot's response, or be in always listening mode. In the next version of FarmChat, we plan to use a custom solution wherein the user needs to speak with a button being pressed, similar to a walkie-talkie. On releasing the button, the speech would be submitted for processing. This would not only solve the premature submission issue, but would also help with the interaction ordering problem experienced by the illiterate participants.

Hardware buttons (e.g., volume controls) could be enabled to provide inputs. All these possible solutions need to be tested in future deployments.

Anthropomorphism: In spite of the lack of any anthropomorphic features in FarmChat, participants assumed that they were interacting with a human. In the future, it would be interesting to explore the use of an agri-expert character to understand how anthropomorphism impacts the conversation. Participants also wanted to use the app in the future in their free time to gain more knowledge. This would move from a 'search' to a 'browse' type of information seeking, which hints that a role of more general virtual 'companion' is possible.

No Reliance on a Wizard: According to the 2001 Census of India, India has 22 official languages, 122 major languages, and 1599 other languages [17]. In rural India, the local languages have a major influence on spoken

Hindi, including accent and word adoption. This results in poor accuracy by Google translation and transcription services. For instance, Google translates the spoken phrase '*faala maar diya*' to 'slapped' (in English), however it actually means '*hit by fog*'. The reason for this error is that '*faala*' is not a Hindi word, but is adopted from the local Khortha language. Similar errors have been previously reported [11]. Background noise from machinery (including tractors and water-pumping motors) and village festivities further adversely affected the speech processing performance. In our user study, we opted for a wizard to fix such issues to understand the usability and information acceptability of a chatbot-based solution for farmers. In the future, we aim to develop a completely automated system. One solution is to develop a custom Speech-to-Text and translation service, possibly on a limited set of keywords, for the specific geography that we are targeting (similar to [11]). Another solution would be to use the recently proposed crowd-powered conversational assistant to automate itself over time [21]. This might be challenging as we may not find enough crowd workers with the knowledge of the local language.

Image-based Diagnostics: Along with speech, FarmChat can be enabled to provide image-based input. This is similar to existing plant pathology apps [1], wherein a farmer is supposed to click a picture of the infected crop and the app predicts the disease name and recommends medicine. However, our agri-entrepreneurs and agri-experts found the accuracy of such apps to be really low. In our case, we can combine the speech-based description of the symptoms with the image-based features, which could improve diagnostic accuracy.

Hyper-local Information: The information provided to the farmers needs to be localized, considering climate conditions, soil type, and market availability. To ensure such information is in place, FarmChat needs to collect it from local partners and domain experts, and add to its knowledge base. Moreover, FarmChat needs to support more crops, specifically 'new' crops. Adopting from the core idea of Digital Green [15], we can develop a knowledge base from farmers who are experts in one such 'new' crop and disseminate that information using FarmChat to farmers in need of that information. Chatbot offers a scalable solution to iteratively expand and customize the knowledge base with expert input and disseminate the knowledge to wide audience.

7.2 Limitations

We acknowledge several limitations of this work. First, the results should be interpreted based on some specificities of the study, including the relatively small sample size, users' first encounter with a chatbot, and the task scenarios used. The positive user responses and other conclusions should be validated by future, preferably longitudinal studies. Second, the knowledge base was developed with the help of only two local agri-experts, due to the limited resources of the NGO we worked with. The performance of the system could be further improved by adding more agri-experts. Third, besides the limited capabilities of speech-to-text and language translation technologies, which we fixed with a human wizard, FarmChat could also fail due to limited access to Internet in rural India as the core technologies are offered as cloud services. Fourth, we need to conduct system-level analysis, such as scalability testing, power measurement, *etc.* in future work before scaling the proposed solution to masses. Finally, although participants showed high trust in the initial encounter, errors and inaccurate information in daily usage can lead to distrust of the system. We also note the potential risk of disseminating inaccurate information at scale with chatbot technologies. So the knowledge base should be carefully developed and reviewed by subject experts.

8 CONCLUSION

Building a scalable, always available and real-time responsive system that satisfies the information needs of rural farmers is an open problem, and one that has significant impact in an agriculture-dominated economy like India. To address this challenge, we proposed FarmChat which combined conversational and language technologies to naturally converse with farmers in answering their farming-related queries. The conversational intelligence of the chatbot was informed by analysis of large corpus of farmer call center logs and guided by agri-experts who work closely with farmers. Our study with 34 potato farmers in rural India indicated that it is possible to provide satisfying information support to the farmers through chatbot. We also compared the effectiveness of two interface modalities: Audio-only and Audio+Text. Our study indicated that although text-based output allows for repeated consumption of the same information, participants expressed different preferences due to literacy, digital-literacy, and other environmental and physical factors. The positive feedback of the farmers indicates that conversational intelligence as a technology delivered through the ubiquitous smartphone can be an effective tool to improve information access in a rural context for people with limited literacy and technology experience.

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