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Large language models and agricultural extension services

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Several factors have traditionally hampered the effectiveness of agricultural extension services, including limited institutional capacity and reach. Here we assess the potential of large language models (LLMs), specifically Generative Pre-trained Transformer (GPT), to transform agricultural extension. We focus on the ability of LLMs to simplify scientific knowledge and provide personalized, location-specific and data-driven agricultural recommendations. We emphasize shortcomings of this technology, informed by real-life testing of GPT to generate technical advice for Nigerian cassava farmers. To ensure a safe and responsible dissemination of LLM functionality across farming worldwide, we propose an idealized LLM design process with human experts in the loop.

Agricultural extension and rural advisory services—also known as agricultural extension, extension services or advisory services—are programmes designed to disseminate new knowledge and the results of scientific research to rural farmers and other stakeholders in the agricultural sector. These services aim to improve the efficiency, productivity, profitability and sustainability of agricultural practices and, ultimately, enhance food security and livelihoods[1]. Concomitantly, agricultural extension plays key roles in facilitating the sharing of farmer experiential knowledge across agro-ecologies. Agricultural extension relies on public and private sector agents—that is, trained professionals working to provide farmers with a range of learning opportunities, information and resources related to their production and marketing activities. Agriculture ministries in developing economies typically invest in setting up extension services alongside, or as part of, their national agricultural research systems (NARS).

Many emerging markets involve large-scale public sector agricultural extension. China alone is estimated to have over 600,000 extensionists[2]. The past few decades have also seen private agricultural extension offered to farmers for a fee, or as a service associated with particular products sold by agrifood companies. Public or private sector agents may conduct training, demonstrations or field visits to share new advances and practices[1]. While it is difficult to determine the number of farmers aided by agricultural extension, these services intend to reach and benefit the small-scale farming community, numbering some 570 million smallholders[3] who cultivate 24% of the world's agricultural land, and produce 29% of the world's crops by kilocalories[4].

Previous experience has shown mixed effectiveness of agricultural extension in both so-called Global North and Global South settings. In India, a regional rice bowl, a review of the National Agricultural Extension Project indicated some satisfactory results helping to improve the adoption of sustainable agriculture practices by smallholder farmers[5]. However, the overall outcomes, sustainability and institutional development—key measures of success for a project—were deemed modest to unsatisfactory[6]. The National Agricultural Extension Project, a noteworthy, multi-stage programme of the World Bank, was also deployed in Tanzania, with more uncertain results[7]. Beyond anecdotal evidence, overall estimates have been highly variable, showing 13–500% rates of return on investments in agricultural extension[8]. The Política Nacional de Assistência Técnica e Extensão Rural, or the National Policy for Technical Assistance and Rural Extension, was established by the Brazilian government to support the development of the rural sector. Although the programme's objectives have not been fully realized due to operational challenges such as staff shortages, overburdened personnel, low wages and unstable conditions in some regions, the programme has shown notable progress in assisting family farmers compared with earlier rural extension services in Brazil[9]. In Ethiopia, while the growth

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of agricultural extension systems has been praised as the fastest and largest in Africa[10], public investments in agricultural extension systems have been inefficient[11].

We can attribute these mixed results to at least five persistent impediments that prevent farmers from accessing or benefiting from agricultural extension. First, many smallholders, particularly those in the Global South, may have limited access to scientific knowledge about new technologies and best practices due to the inadequate reach of existing extension services, often exacerbated by poor infrastructure such as roads, electricity and internet connectivity[12].

Language is a second limitation. Across the globe, there is remarkable linguistic diversity, as shown by the existence of 492 institutional, 3,593 stable and 3,072 endangered languages, reflecting the vast array of major and minor languages and dialects that are used across institutions, communities and households[13]. Extension services may be delivered in a language or dialect that is not understood by some farmers, or the messages may be irrelevant to their needs.

Third, farmers, especially smallholders, may have limited time and resources to attend training sessions or workshops, or to travel to agricultural extension centres to receive scientific advice and support. A fourth limitation is related to institutional capacity[14], particularly in developing economies where extension services are often underfunded and understaffed. This makes it difficult to reach large numbers of farmers at once, and many extension agents are poorly trained, with little (if any) continued professional development opportunities to keep their knowledge current[12]. Finally, conventional extension services have tended to provide generic information based on the agro-climatic region, rather than providing personalized information specific to the weather and soil characteristics of the individual farmer, thereby limiting its case-specific relevance and impact.

Beyond these five persistent impediments, there are several other challenges to consider, including supervising extension agents in remote rural areas, the need for providing advice while keeping user privacy and addressing accessibility biases towards specific farmer profiles[15].

These issues are not restricted to developing economies alone; more attention to non-traditional extension approaches including group extension and farmer-led extension[16], and emphasis on the 'back-office' for technology monitoring, training and generation and management of technical knowledge can improve outcomes for farm advisory services in Europe[17].

To address the challenges of access, use and scale of agricultural extension in diverse geographical regions, computer hardware and software are increasingly being developed and deployed, including virtual extension services, mobile device applications (apps), agricultural information systems and social media platforms[2]. For example, agricultural extension programmes have developed apps that provide farmers with access to advice on a range of topics, including crop management, animal husbandry and market prices. The Food and Agricultural Organization of the United Nations (FAO) Technologies and Practices for Small Agricultural Producers (TECA) platform gathers successful practices to facilitate knowledge exchange and help smallholders in the field. In another example, the Virtual Extension Service for Agriculture in India uses online resources to reach smallholders across the country[15]. Similarly, Plantix[18] and PlantVillage Nuru[19] are mobile phone apps designed to support farmers and agricultural advisors with in-field identification of crop pests and disease using computer vision and community-driven image sharing and annotation. Plantix reports that they are processing over 50,000 images a day across 30 crops, supporting 18 languages[20]. PlantVillage reports that their applications are used by the FAO in 60 countries and in 30 languages[21].

There are hundreds of platforms, apps and approaches similar to those mentioned here. Yet, while most virtual extension services offer very generalized recommendations, farmers typically require specific advice[15], for example on the varieties most appropriate for their area given seasonal forecasts, the herbicides most suitable to control specific weed species that have appeared in fields or precise fertilizer regimes and application timings for their soil fertility conditions. Language models hold the promise of improving both the process of identifying and synthesizing the results of scientific research and continually improving, context-specific, personalized conversational interfaces to deliver highly personalized agricultural advice at scale.

Moreover, smallholders often cannot access physical extension services and digital extension services also struggle to reach scale[22] due to scientific and technical limitations, including low digital literacy and low levels of internet experience among smallholders, language limitations and the capacity issues detailed above. Such problems persist despite internet penetration and access increasing worldwide, as are ways of delivering information via low-tech alternatives such as short message service (SMS) and interactive voice response (IVR) to those with poor or no access to internet[22,23].

Against this backdrop, in this Perspective we examine the potential of an emerging human–machine interface, ChatGPT, which is based on Generative Pre-trained Transformer (GPT), to surpass these limitations and advance extension services substantially. Leveraging large language models (LLMs), ChatGPT is a nascent, but seemingly potent, application of artificial intelligence (AI). LLMs are specific types of AI that are trained on massive volumes of unlabelled text data to learn patterns and contextual relationships among words. Notable examples of LLMs include ChatGPT by OpenAI, LaMDA by Google, LLaMA by Meta and Megatron-Turing by Nvidia and Microsoft. While each of the models mentioned has unique strengths and capabilities, ChatGPT has several features that set it apart, and for which it was selected as the focus of this study. In terms of scale, ChatGPT is one of the largest publicly available LLMs, with to 175 billion parameters (for GPT-3). This makes the model more powerful than others. In terms of training data, ChatGPT has been trained on a diverse range of sources, including web pages, books and articles from a variety of domains. This enables the model to generate responses on a wide range of prompts, and to understand and use language in more nuanced ways. With regard to flexibility, ChatGPT can be fine-tuned to specific knowledge domains and tasks, making it more adaptable to specific use cases than most other LLMs. In addition, ChatGPT can be easily integrated into a chatbot or conversational agent, allowing it to interact with users in real time. This makes it a valuable tool for organizations looking to improve user support.

Among its envisaged benefits for agricultural extension services, we focus on the ability of ChatGPT to simplify scientific knowledge and provide personalized, location-specific and data-driven recommendations. Informed by real-life interrogations of this LLM by a team of agricultural extensionists, agronomists and modellers in sub-Saharan Africa and South America, including Nigerian cassava farmers, we discuss shortcomings of the technology and emphasize a few deployment barriers that are yet to be explored. We argue that digital extension services will fail without strong, continued focus on open-access, machine-readable agricultural knowledge, user-centred design in ultimate delivery mechanisms and an agenda driven by problem orientation[24]. We conclude with a call to improve the human–machine interface, and propose an idealized LLM design process with human experts in the loop. In doing so, this Perspective aims to add additional reflections to the emerging debate of this topic among the extension science community[25,26] and generate momentum towards responsible deployment of LLMs in agricultural extension for the better.

Agricultural extension and state-of-the-art LLMs

ChatGPT is a chatbot built on the GPT architecture, specifically designed to generate human-like text in conversational settings with humans. This chatbot is based on the transformer model, a neural network architecture that performs a variety of natural language processing tasks. The GPT architecture consists solely of a decoder composed of multiple layers of interconnected 'attention' and 'feedforward' modules. The decoder processes the input text and creates a representation of it, which is then used to generate context-aware output text in the form of conversational responses[27].

The layers of self-attention encompassed in the architecture of ChatGPT help to enable the algorithm to consider the context of the conversation when generating responses. It also includes a special 'persona' input that enables the model to maintain a consistent identity during each conversation. The algorithm is trained on a large dataset of human–human conversations to learn the patterns and structure of natural language conversations. ChatGPT has an array of possible multimodal applications, such as chatbots, language translation software, automated content generation and virtual assistants—all of which are generating discussion and excitement in the context of agricultural extension. For example, dedicated academic journals have recently published editorials inviting the scholarly community to focus on topics in this space[28], while online magazine outlets have begun hypothesizing on whether ChatGPT can "revolutionize agriculture"[29].

While critiques of LLMs and GPT are numerous, including issues of ethics and representation[30], this fundamental capability to develop human-like language and intermediate between dynamic communication and a given corpus of knowledge could prove to be transformative in the long run. In this vein, we expect current and near-future GPT models to support the work of agricultural extension institutions directly and indirectly, by reaching more farmer populations and by enhancing extension agent capabilities. We envision that this could be transformative in at least two ways: simplifying scientific knowledge and generating personalized data-driven recommendations.

Accessibility of scientific knowledge

GPT could be trained to explain—in simple terms—complex agronomic, botanical and hydrological knowledge to extension agents or digital-savvy (typically wealthier) farmers. By generating plain language summaries of research articles and scientific reports, state-of-the-art knowledge in plant or soil sciences such as precision nutrient management could become accessible to extension agents and other stakeholders, enabling them to stay current and propose or practice better-bet options.

For instance, farmers or extension agents might not have the time, background knowledge or scientific training to read through a lengthy, technical report on the latest scientific advances in integrated pest management, nor may they be aware of or have access to such literature. GPT can distil key points from relevant publications and, through rapidly advancing translation technology, present them in accessible language that is easier to understand and apply on-farm.

With human expert intervention to ensure accuracy, fine tune and add missing details[31], the GPT model could be trained to generate a variety of content for extension services, such as research syntheses, fact sheets, articles and 'text-bites' (Box 1). This could help extension services to not only educate themselves on new advances, but also efficiently disseminate more relevant information and advice to farmers and other stakeholders. GPT can analyse literature and data about specific issues related to smallholder farming and generate location-relevant content on those topics.

Exemplar topics in this context include suitable crops to diversify cropping systems or assure permanent soil cover, interventions to minimize soil loss, agronomic management options and climate adaptation and mitigation measures.

If this technology is coupled with human expertise, agricultural extension institutions could use it to reduce the time involved in synthesizing content and adapting it for specific farmer-facing distribution channels such as SMS messages, video scripts and radio broadcasts.

While ChatGPT and allied technologies cannot be used as a direct solution for extension services today, they could be helpful in developing content faster for dissemination to a large number of farmers when they need it most. If combined with translation software, ChatGPT may also bypass the language barriers highlighted above. An early example of this is Kissan GPT, a multilingual AI chatbot designed to offer tailored assistance to farmers in India. LLMs can radically improve the effectiveness of back-office activities that include training advisors, and access to targeted, evidence-based knowledge[17]. Coupled with chatbots such as Kissan GPT, which represent a new 'front-office' model for extension services, LLMs can help reduce the disconnect between the traditional extension front office (the human network) and back office (including advisor training, knowledge collection, advisory production and so on).

BOX 1

ChatGPT-based messages for controlling fall armyworm

Here a team of extensionists and agronomists tasked ChatGPT (GPT-3; on 13 February 2023 using the 2023 version accessed via the OpenAI web-interface) with creating messages with a 160-character limit for controlling fall armyworm (FAW) (*Spodoptera frugiperda*), which can decimate maize. The LLM generated advice that was not specific enough to provide guidance on recognizing a FAW-infested crop or to tailor advice to specific locations or weather conditions. This example highlights the need for the current GPT model to be tuned within broader contexts. When the same task was assigned to Microsoft Bing (powered by ChatGPT and accessed 5 March 2023), it returned more detailed responses with specific citations:

GPT-generated SMS 1: Check your maize plants often for FAW signs. Look for holes in leaves, eggs under leaves, and caterpillars inside stems. Use traps with FAW smell to catch them early. Spray small caterpillars with chemicals that stop them from growing.

GPT-generated SMS 2: Use different types of chemicals to kill FAW. Some good ones are emamectin benzoate, acephate, indoxacarb. Read the labels carefully and follow the instructions. Don't use too much or too little.

GPT-generated SMS 3: Use other ways to control FAW besides chemicals. Plant different crops together or after each other. Plant Desmodium and Napier Grass around your maize field. Use wasps that lay eggs inside FAW caterpillars.

Although it does not provide context-specific information, and may be deemed imprecise ('Don't use too much or too little', SMS 2), the integration of an LLM with the internet could leverage vastly more information (for example, compared with informational brochures) and offer substantial advantages compared with a model that only has access to a limited database. This should guide the LLM development process.

Personalized data-driven recommendations at scale

The ability to rapidly interface between real language, a corpus of relevant agricultural knowledge and emergent research coupled with agricultural data science and agro-climatic forecasting could be a potent tool for fostering farming system productivity and resilience. However, as mentioned above, technology that can source and process data and run crop models to localize and contextualize foundational training sets of textual corpora over which LLMs act does not yet exist. Most agricultural extension services disseminate and aim to improve on a fairly standard 'package of practices' by crop and agricultural zones, including access to good-quality seeds, chemical inputs and other advisory content that is relevant to farmers' challenges. However, these challenges cannot be tackled in a 'one size fits all' manner, as farmer needs and constraints differ based on factors including personal motivations, innovation objectives and resource endowments.

LLMs offer the potential for more nuanced support by learning from location-specific knowledge corpora.

For instance, conversational chatbots such as FarmChat and Kissan GPT were developed by incorporating the knowledge derived from the Indian Kisan Call Centre dataset and inputs from agri-experts. Such models require labelled training data in an input–output or question–answer format. Application of LLMs over domain-specific datasets, such as agricultural research articles, could overcome this tedious training process by learning from the text in its current unlabelled format, but the models still need to be supervised and verified by humans in the loop.

With improved technical capabilities, expert curation and feedback, and a growing corpus of training data (not just publications) including geospatial data, analytical models and the array of preceding digital agriculture technologies[32], GPT might be used to draw on the results of analytics-driven recommendation frameworks to provide data-based responses to questions such as 'How much fertilizer should I apply to my cassava crop to realize a yield of crop-X tons per hectare?' This response would ideally consider the farmer's location (relevant for soil, weather and market conditions), but we are still far from such capabilities, which will require technology advances, large corpora of open data adhering to FAIR Principles[33]—findability, accessibility, interoperability and reusability—and improved human–machine interfaces at minimum.

Providing such advances, GPT might also be used to synthesize data about farmers, including information about farm operations, agricultural input usage preferences and patterns, and environmental, economic and market conditions. By converting these data into easily understandable language—and always with humans involved in validating outputs—GPT could facilitate communicating improved personalized recommendations for growers that are appropriate to their specific needs, technical levels and circumstances. Incorporating the conversational history between the chatbot and each farmer can further enhance the chatbot's ability to generate tailored recommendations, as it allows the system to continuously learn and adapt to the individual's specific needs, preferences and context. With this added benefit, GPT-based applications can provide even more accurate and relevant guidance to farmers, fostering better decision-making and improved farm management practices. Chatbots serve as a convenient interface that can be accessed anytime and anywhere, benefiting farmers and extension agents who may have limited time and resources to attend training sessions or workshops. Finally, there are several agricultural extension solutions that leverage computer vision, such as Plantix and PlantVillage Nuru, which are deployed on mobile phones to assist growers and crop advisors with assessing plant health and accessing relevant services. LLMs hold the potential to become a human–machine interface, a powerful force multiplier to such efforts, especially in recent iterations that include multimodal and image processing (for example, GPT-4).

BOX 2

Limitations of ChatGPT in weed control in Nigerian cassava farming

Here ChatGPT (GPT-4; 16 March 2023 using the 2023 version accessed via the OpenAI web-interface) was asked to generate recommendations to control weeds by a team of extensionists, agronomists and modellers, including Nigerian cassava farmers and experts from Africa Cassava Agronomy Initiative. The chat thread included four consecutive prompts as follows: (1) 'I am a Nigerian cassava farmer, how should I control weeds?'; (2) 'Which herbicides are best suited for chemical control in Nigeria?'; (3) 'Can you provide brand names and specifics on the application dose and method?'; and (4) 'Can you create 5 SMS based on the above advise and suggest when to send the SMS?'. Responses to these prompts are included in the Supplementary Information.

In cassava cropping systems, pre-emergence herbicides need to be applied immediately after land preparation and planting (within 24 hours). If the cassava started sprouting, then the herbicide will damage or destroy the crop. Post-emergence herbicides should not be used within the first 5–6 weeks after planting, and when used, especially if the crop is still young, a spray shield should be used. If land preparation is done well, and a pre-emergence herbicide is used, no manual weeding may be needed; but if rainfall is heavy or weed pressure is high, a manual weeding operation may not be avoidable. In this context, GPT's responses are insufficiently accurate, at the risk of crop loss. SMS 2 and SMS 3 were both wrong in terms of application timing. SMS 4 and SMS 5 were too generic (Supplementary Information). The advice on mulching (replies to prompt 1, 2, and SMS 4; Supplementary Information) was not incorrect, but not practicable for smallholders, who do not have access to the quantities of straw or other organic residues to implement this. Intercropping (reply to prompt 1; Supplementary Information) is a common practice, but will generally also result in yield reductions for the cassava crop, and requires careful consideration of the choice of variety types, crop arrangement and crop density. This serves to point out that GPT gets some of the essence, but the output is certainly not appropriate to use 'as is', and it generally remains too generic and insufficiently hands-on to be of use to farmers or suitable for extensionists to pass on.

Assisting the virtual assistants

While we assume a swift and at-scale deployment of GPT-based extension services, such deployment is not free of challenges and risks. Indeed, while GPT applications have the potential to improve agricultural extension, several of the impediments of conventional extensions services introduced above persist as challenges, while new risks specifically associated with AI arise in this context.

First, a critical point of potential failure is the lack of a high-quality, well-validated open and interoperable set of publications for GPT and similar LLMs from which to train. Unsurprisingly, scientific literature also tends to be highly variable and could result in misdiagnoses and erroneous advisory outputs—with potential for harm at a greater scale than is possible through existing agricultural extension pathways. The risk of unfounded advice has been recognized before[34], and unvetted LLMs may compound it. Even with a good-quality corpus of publications, including peer-reviewed studies, LLMs can generate results that are factually inaccurate or impracticable (Box 2).

Future advances may include AI approaches that combine the strengths of LLMs with the ability to derive more location-specific agricultural insights from data. This will require large amounts of open and interoperable data, and proper institutional funding and facilitation. Consortium of International Agricultural Research Centers (CGIAR) centres and other agricultural research and development entities are making progress in this regard, but it will take greater commitment than is evident at present. There is strong evidence that publications from CGIAR and other organizations were used to train the GPT models, emphasizing the importance of open-access publications[35].

As AI in agriculture moves beyond publication towards leveraging data, good data governance practices that address issues of data ownership will become critical in this new landscape. Data governance ensures that data assets fully remain widely available and interoperable, and are also secure, trustworthy and not misused, while tackling questions of ownership[36]. Data cooperatives offer a model for governing farm data, with an emphasis on empowering farmers in relation to data ownership. Several examples exist in the United States, such as the Ag Data Coalition, the Grower Information Services Cooperative and the Farmer Business Network, and similar approaches are emerging in developing countries through efforts of entities such as Digital Green (https://farmstack.digitalgreen.org/), Yara and IBM. Such efforts will help farmers to securely share data while retaining decision-making power on who uses and benefiting monetarily, as well as helping increase the corpora of data and knowledge products for LLMs to act on.

Data interoperability and machine readability offer their own challenges, but there are already ways in which these challenges may be tackled. The consistent use of community ontologies such as the Agronomy Ontology (CGIAR's AgrO) that respond to Open Biological and Biomedical Ontology (OBO) Foundry Principles confer semantic interoperability when used to annotate data. Such interoperability enables data to be machine-readable, enhancing search retrieval and data science approaches to formulate appropriate interventions. Ontologies are formalized schemas that enable classification and organization of concepts in a domain, providing semantic context through explicitly stated relationships and hierarchies among the concepts, or terms. Every term is associated with a uniform resource identifier to identify resources and clarify to machines what the term means and the broader context in which it resides based on its place in the hierarchy—this provides advantages for AI that moves beyond publications to data.

A related concern is that LLMs like GPT may be less relevant in the so-called Global South, where agricultural advice may be needed the most. Agricultural challenges prevalent in the Global South and their associated scientific knowledge might be under-represented in the training datasets used in ChatGPT-like applications. In the same vein, generating personalized, data-driven recommendations or training programmes for farmers and other stakeholders using applications like ChatGPT necessitates systematic efforts for collecting, storing and analysing data about farmers and other stakeholders. It also assumes that location-relevant, machine-interpretable agricultural knowledge is available in the public domain, along with reliable internet access.

Second, physical access (for example, roads) and information and communication technology (ICT) infrastructure (for example, 4G network coverage) in low- and middle-income countries of the Global South are generally underdeveloped, widening the gaps between commercial farmers and subsistence farmers. In areas with limited internet access, GPT-based extension services would be more difficult to implement, but even in these circumstances it may be possible to find alternative ways to use GPT or other LLMs to support the work of extension services. For example, where rural areas have no network coverage and poor physical access to extension services headquarters, GPT-based applications could be used by extension services headquarters to generate content that could be printed and distributed to farmers and other stakeholders. Where rural areas have basic networks but lack high-speed (for example, 4G or 5G) coverage, GPT-generated advisory content could be disseminated by extension services via radio and text messaging. The specific approach would depend on the local context and the resources and infrastructure that are available.

CGIAR's African Cassava Agronomy Intensification project and Excellence in Agronomy Initiative are following similar models, disseminating crop management advice through scaling partners comprising public–private partner associations and relying on radio, television or visual materials. Existing content for one channel can be rapidly adapted to another channel. For example, a section from an agricultural extension manual could be turned into a script for an instructional farmer-friendly video, or a dialogue between a farmer and an extensionist for a cartoon guide. Advancements in text-to-image and text-to-animation/video technologies have the potential to substantially reduce the cost of producing such content, which currently requires thousands of dollars of production cost per minute, making the creation of these materials more accessible and affordable. Outputs from LLMs may also be delivered via SMS, IVR or other low-tech channels, making data-driven advisory content accessible even for those with limited internet connectivity.

Third, addressing language barriers should be prioritized given the thousands of languages and dialects spoken across low- and middle-income countries. While GPT and other LLMs are designed to work across multiple languages, performance may vary depending on the quality of the training data. In general, such models are more effective for languages that have a large amount of high-quality training data available, which generally means that GPT is likely to be most effective for English, the lingua franca of science.

For languages with smaller amounts of training data, or for languages with complex grammatical structures or other linguistic features, LLM performance may be less effective. Erroneous extrapolation of agricultural interventions from the context for which they were developed to a different one could adversely affect the livelihoods of farmers with little or no ability to bear risk.

Fourth, even if sufficient training data are available, sufficient ICT infrastructure exists and language barriers can be resolved, the use of GPT-based extension services is likely to be low among smallholder farmers who lack digital acumen. While GPT technology has notable scope for reducing the time cost of content creation amongst extension agents, the effectiveness of that content will be limited if the recipient farmers lack the basic level of digital literacy required to comprehend, interpret and critically assess the quality of information provided.

Moreover, due to existing cultural inequalities, women and other marginalized communities may have difficulty accessing information through ICT technologies, thereby exacerbating digital divides and excluding certain segments of the rural population from the benefits of GPT-based extension services.

Finally, the development and deployment of GPT and other LLMs in extension services should be carefully validated via in silico and in situ analysis and testing across agro-ecosystems before the technology is embraced globally. Indeed, testing of emerging technologies across agro-ecosystems, and learning to improve future deployment, has long informed the governance of scientific discovery, yet often through a retrospective, ex post facto approach where the effects of a research output are examined and determined to be harmful[37].

Responsible research and innovation (RRI) approaches to technology design and dissemination include dimensions of anticipation, reflexivity, inclusion and responsiveness. These address a range of institutional concerns spanning foresight, technology assessment, ethics, user-centred design, standards, open innovation and others. RRI thus offers a systematic framework to assure a safer, more sustainable alternative to the reactive or retrospective approach common in research and innovation[37,38], and it has a history of uses in the digital agriculture domain[39].

RRI is critical in relation to LLMs, and part of the RRI framework in this respect might include early implementation of LLMs in 'digital sandboxes'. Digital sandboxes are low-risk, hybrid, socio–cyber–physical spaces where initial deployment of LLMs can be observed and studied. In these safe spaces, various institutional stakeholders—including, for example, CGIAR extensionists and farmers—may supervise prototyping and piloting of novel techniques, ensuring that they are safe before moving to deployment. Such hybrid spaces allow a safe playground for emerging technologies, and have been proposed for other types of agricultural AI[40], such as Agbots and decision support systems.

To ensure that in silico and in situ assessment and testing of LLMs, including GPT models, are carried out we propose an idealized LLM design and deployment process. This process was developed through an iterative, participatory processes involving extensionists, agronomists, modellers, engineers from across four CGIAR centres, the Linux Foundation and academia, including AI risk analysts from the social sciences, natural sciences and engineering science (Fig. 1).

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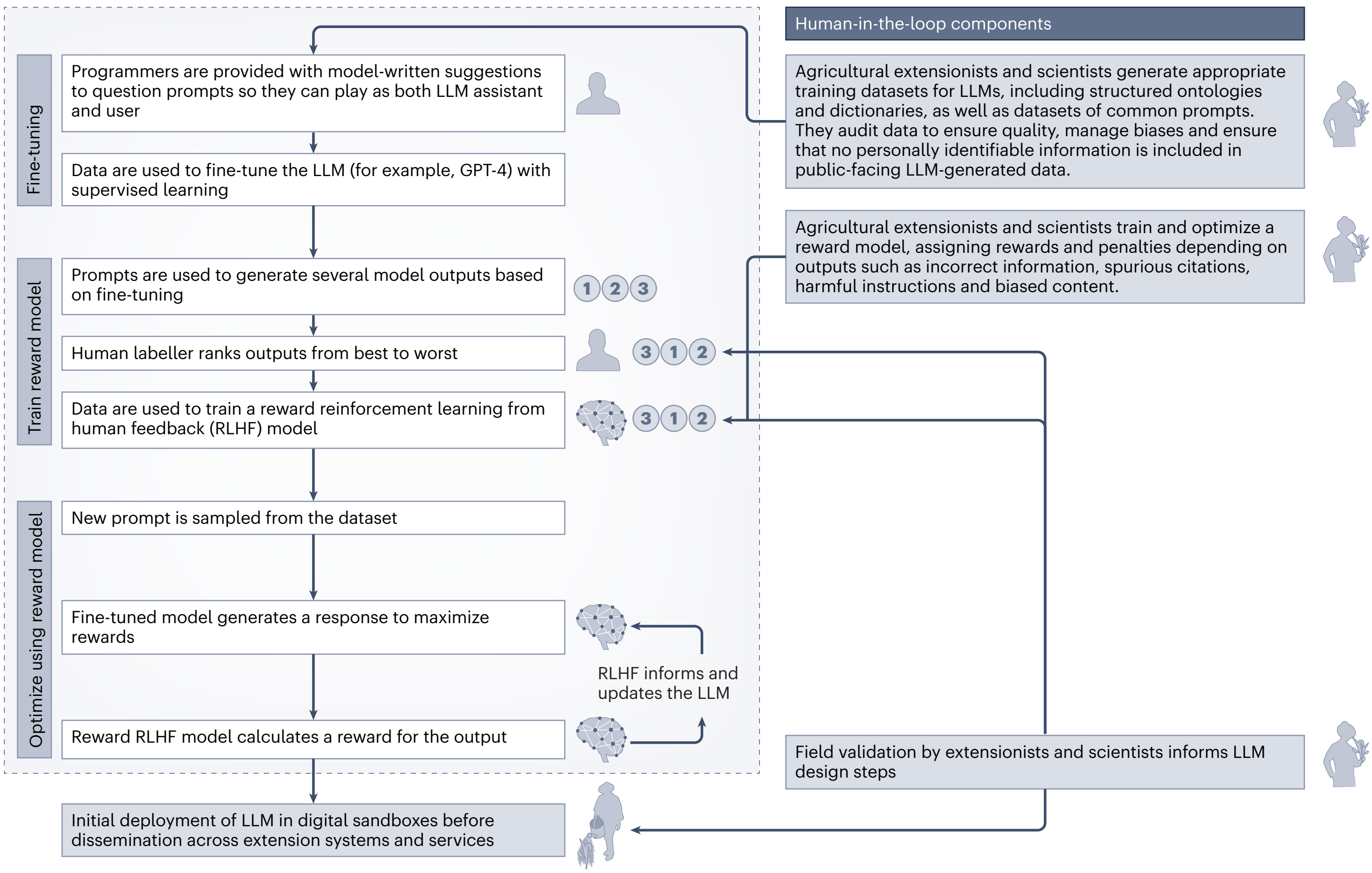

Fig. 1 | Idealized LLM design and deployment process for agricultural extension systems with humans in the loop. This process was created and validated in an iterative, participatory process by agricultural scientists, agronomists, modellers, engineers and computer scientists from three CGIAR centres (International Institute of Tropical Agriculture, International Center for Tropical Agriculture and the International Food Policy Research Institute), CGIAR's Platform for Big Data in Agriculture, the Linux Foundation, Cambridge Department of Engineering, Cambridge Centre for the Study of Existential Risk and the Cambridge Global Food Security Centre. The dashed box contains a general development process for LLMs, including ChatGPT, comprising eight steps. The numbers in circles represent GPT model outputs (answers). Here this process is modified with four 'human experts in the loop' components. At the very minimum, 'extensionists' should include an agronomist specializing in agroecology, a plant health/plant pathology expert, a water or soil resources expert and a communications specialist of some sort. It is also advisable to include a sociologist, a usability expert and a markets specialist. Similar loops could be established for complementary domains, as LLMs can absorb and integrate inputs across domains.

The way forwards

LLMs, including ChatGPT, are technologies that have potential to advance the impact of agricultural extension—and consequently food security—locally, regionally and globally. ChatGPT-like applications could make extension services more accessible and relevant to a wider range of farmers if purpose-driven training and design are implemented by designated institutions, including CGIAR and national extension agencies, to overcome existing limitations and address systemic issues, such as the lack of access to information.

Nonetheless, it is critical to consider the risk of farmers being provided bad or unvetted advice, given the potential for rapid and large-scale dissemination of imperfect and still-in-development LLMs. GPT's agricultural outputs should therefore be stringently validated in a range of farming systems and scenarios before the technology is deployed. While there may be barriers to deploying such technologies in regions where ICT infrastructure is underdeveloped, these may be overcome by the complementary use of low-tech delivery channels and efforts to improve ICT infrastructure.

The dynamics of LLMs in agricultural extension services are complex. A number of issues explored in this Perspective, as well as the potential roles and incentives of various parties (private, public and nongovernmental) that could offer GTP-based solutions, handle and prevent possible ramification of LLMs for agricultural extension services – and how 'heavily' should human supervision be exercised in each GPT-based digital extension – warrant further attention by the academic and practitioner communities.

As AI technologies advance and open, and interoperable data becomes the norm (rather than the exception) in agricultural research, tools like ChatGPT could become more reliable and safer to deploy—and are then likely to be increasingly used to overcome current gaps in extension services to provide location-specific information. In due course, the use of ChatGPT in agricultural extension services has the potential to improve the productivity and profitability of farmers, as well as the sustainability of agricultural systems, in a cost-effective and scalable manner. However, given the current state of the technology, and without large corpora of machine-interpretable open-access data and knowledge nor human oversight for quality control and verification, there is potential for harm if GPT and similar AI solutions go to farm—particularly to smallholders in low- and middle-income countries where the ability to tolerate risk is low to non-existent.

AI tools like ChatGPT can offer valuable support to human extension services in agriculture, as well as help make them more efficient, and address some infrastructure and capacity gaps. At the same time, we believe AI systems are unlikely to replace the knowledge, experience and trust that human experts have built with farmers. Instead, AI-driven insights can complement and enhance the services provided by extension officers, enabling them to provide more accurate and personalized guidance to farmers. By incorporating farmer experience, extension officers can contribute to training chatbots, creating more efficient, effective and accessible agricultural extension services. As AI capabilities improve, the potential for AI to assist human extension officers in agriculture is expected to increase. Advancements such as improved natural language understanding, multilingual support and context-aware reasoning could enhance the accuracy and personalization of recommendations. Ultimately, the partnership between AI and human experts will play a crucial role in addressing the complex and evolving needs of farmers and the agricultural sector.

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