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Large Language Models for Agricultural and Rural Development: An Application of Foundational Models in Extension

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Abstract

This study investigates the applicability, practicality, and effectiveness of a low-cost AI foundational model (FM) in agricultural extension through the development, fine-tuning, and evaluation of a custom GPT named Utah PeachBot, built using OpenAI's GPT platform. The research focused on facilitating real-time, evidence-based advisory service support for Extension agents assisting small-scale peach producers in Utah. Methods involved training the GPT with curated, research-based horticultural resources and assessing model outputs through an expert panel of six Extension agents. Results showed high reliability and accuracy for general inquiries about peach cultivation. However, inconsistencies in regional specificity and the practicality of recommendations emerged as limitations. Feedback indicated a need for iterative fine-tuning of the model through continuous expert feedback and integration of local, context-specific data. Recommendations include a phased approach to implementing customized GPTs in agricultural advisory services to improve information dissemination, decision-making quality, and operational efficiency within extension systems.

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Introduction and Literature Review

Information dissemination has been a longstanding function of extension and was a central tenet of the technology transfer philosophy (Koutsouris, 2018). Even as extension shifted from a technology transfer to decentralized, participatory knowledge exchange, information dissemination remains relevant. Khan et al. (2025) provided a scoping review of 131 articles on extension's pursuit of modern methods to transform the one-way nature of information dissemination into a manner that facilitates farmers as active participants in the knowledge exchange process. The literature provides many examples of innovative approaches to strengthening linkages between farmers and extension (e.g., Mapiye & Dzama, 2024; Swanson & Rajalahti, 2010). ICTs have been at the forefront of the literature on extension methods (World Bank, 2017; Xu et al., 2023); affecting how extension generates, compiles, and shares data with agricultural innovation system (AIS) stakeholders (Saravanan, 2010). The Food and Agricultural Organization (FAO) outlined how ICTs have changed farmers' interaction with extension (FAO, 2017). As such, ICTs have facilitated extension's transition from a top-down model to a decentralized participatory model through knowledge co-creation and sharing.

Moreover, the emergence of generative artificial intelligence (GenAI) has changed how society develops, curates, and interacts with data to produce knowledge (Banh & Strobel, 2023). Law (2024) described GenAI as a machine learning model that synthesizes big data using deep learning (DL) into organized content. ChatGPT was one of the first GenAI models freely available to the public, and others like LLaMA, Claude, Gemini, and Perplexity quickly followed. These large language models (LLMs), referred to as Foundational Models (FMs), are trained on large datasets for decision-making and content creation (Li et al., 2024; Moor et al., 2023). According to Schmidgall et al. (2023), FMs capitalize on DL using artificial neural networks to produce human-like content, even with zero-shot prompts (which do not require task-specific examples).

With many industries adopting FMs to facilitate complex decision-making, agricultural extension lags (Li et al., 2024; Shaikh et al., 2024). The literature has shifted some attention to GenAI and FMs by outlining its potential for extension advisory services, which signals a precursor to change. Swanson and Rajalahti (2010) provided a comprehensive discussion on how extension has evolved to meet farmers' changing needs. However, in the developing world, extension agents are the primary source of information for small-scale farmers who are typically disadvantaged by the declining yet ever-present digital divide (Antwi-Agyei & Stringer, 2021; Dhillon & Moncur, 2023; Mehrabi et al., 2021). These farmers depend on extension for on-farm decision-making on a range of topics, including climate variability, pests and diseases management, and risk management. In many cases, extension lacks the organizational capacity to serve farmers who are often scattered across remote areas. The estimated ratio of farmers to extension agents in low-and middle-income countries was 1000 to 1 (Davis et al., 2010).

Farmers' satisfaction with Extension is often tied to the frequency of farm visits by agents (Ganpat et al., 2017). Agents are often expected to answer questions in real-time, and their ability to solve problems directly affects farmers' perception of the value of extension (Ganpat et al., 2017; Kassem, 2021; Maake & Antwi, 2022; Somanje et al., 2021). Information provided by agents must be location-specific and personalized based on farm characteristics. Agents are expected to understand a wide range of topics, from climate-smart agriculture to precision farming, to effectively meet the needs of farmers (Lindblom et al., 2017; Nachibi et al., 2024; Suvedi & Sasidhar, 2024). Consequently, small-scale farmers are often reliant on incomplete data to make decisions critical to their livelihoods (Elbasi et al., 2024; Langyintuo, 2020; Smith & Patel, 2023). They depend on key players in the AIS for information (World Bank, 2012). Therefore, FMs are poised to be a significant advancement in agricultural development as they have the capability to generate knowledge quickly from complex data.

Findings from Ibrahim et al. (2024) strongly supported the application of an idealized FM in agricultural extension. Therefore, this study sought to expand the limited literature on FMs in advisory services by investigating the applicability, practicality, and effectiveness of a low-cost FM for agricultural extension in Utah. As a case example, Utah's small-scale peach producers lack timely, county-specific, research-based advisory support for variety selection, pest and disease timing, and irrigation, which limits management decisions and productivity. Therefore, a simple custom GPT, the Utah PeachBot, was designed to serve as a supplementary resource to for Utah State University (USU) Extension agents.

Purpose and Objectives

This study demonstrates a low-cost, domain-tuned custom GPT (i.e., Utah PeachBot) to address the advisory gap facing small-scale Utah peach growers. The objectives are to (a) specify model parameters and instruction design used to localize outputs for Utah peach growers, (b) describe model configuration, knowledge base curation, and deployment workflow, and (c) discuss reliability, accuracy, and satisfaction with the model using feedback from an expert panel of six extension agents.

Methods: Model Development

OpenAI's GPT creation platform (OpenAI, 2023a, 2023b) was employed to develop a customized large language model (LLM) referred to as Utah PeachBot. This model underwent training on curated horticultural materials in GPT-4o, including fertilization schedules, pest management guides, cultivar recommendations, and irrigation practices. The objective was to facilitate real-time, evidence-based responses applicable to small-scale peach producers in Utah. Utah PeachBot was an extension AI tool configured as "*Your USU Extension expert AI assistant for research-based answers to every peach-growing question, from planting and pruning to pest control and harvest timing.*" The GPT was developed as a utility tool for USU Extension agents requiring research-based support in real-time consultations with farmers. The GPT's instructions drew on Birss' (2023) CREATE framework to produce context-sensitive outputs (see Table 1). This framework organizes prompt instructions across six elements: Character, Request, Example, Adjustment, Type of Output, and Extras.

Table 1
CREATE Framework Specifications for Utah PeachBot

CREATE Element	What It Controls	Utah PeachBot Implementation
Character	Assigned role/voice and domain expertise	Assistant role as an assistant and expert peach grower with ~20 years of orchard management experience.
Request	Evidence rules and allowed sources	Generate research-based responses using verified USU-developed factsheets and relevant land-grant university resources only.
Examples	Style/quality exemplars for answers	Model outputs draw inspiration from leading horticultural scientists and established Extension guidance.
Adjustments	Context the model must gather before advising	Prompt users for orchard county, variety/cultivar, whether the orchard is mixed, and whether it is organic; to tailor recommendations.
Type of Output	Format, length, and clarity constraints	Brief, plain-language recommendations, typically as numbered steps or bullet points for quick field use.
Extras	Additional rules, guardrails, and UX cues	Always include a pesticide precaution disclaimer with chemical controls; use conversation starters to elicit location/variety/composition/ organic status up front.

An expert-panel evaluation of Utah PeachBot was conducted during a 1-month pilot (February 2025) with six USU Extension horticulture agents (representing six counties across Utah's diverse microclimates). Agents were selected for active peach advisory roles, variation in climate zones, and experience. The expert panel was asked to identify and organize relevant resources on peach production in Utah from USU Extension and other land grant universities. These sources included guidelines for pest control, fertilization strategies, cultivar selection, and irrigation methods. At the time of development, OpenAI's GPT creation platform supported a maximum of 20 documents. Therefore, only the most essential references were included in the GPT's final knowledge base. The panel contributed frequently asked questions (FAQs) to the model related to pruning, watering schedules, pest control, and cultivar choices based on their experience working with farmers. To generate context-specific outputs, Utah PeachBot was configured to deploy four conversation starters, encouraging users to specify orchard location, variety, orchard composition, and organic status.

The panel documented their queries and recorded observations regarding clarity, accuracy, and alignment with USU Extension guidelines. This feedback yielded preliminary insights into the GPT's capacity to manage diverse peach-related inquiries in practical settings. The authors independently reviewed anonymized conversation logs produced during the pilot phase. Their evaluation focused on the completeness, precision, and reliability of Utah PeachBot's responses compared to recognized extension standards. Testers' comments were then assessed to identify patterns, such as user perceptions of time savings or the need for a broader range of pest and disease resources. Based on these findings, further modifications were introduced. Updated peach cultivation information was uploaded, and prompts were adjusted to consistently include pesticide-related disclaimers.

The Utah State University IRB determined this activity Exempt because it involved evaluation of a decision-support tool by professional staff; no personal information from clients was collected, and all logs were anonymized for external review.

Products and Findings

Utah PeachBot's outputs were evaluated by the expert panel (i.e., testers) during the month of February 2025 and found to be generally accurate for commonly encountered topics in peach cultivation, including pruning methods, selecting cold-hardy varieties, and determining appropriate pest control timelines. One tester found the platform accurate when seeking cold-hardy varieties, while another tester observed consistent alignment with established horticultural guidelines for pruning schedules and pest management. Despite these strengths, specific recommendations (e.g., the mention of Peach Leaf Curl in Hurricane, UT) did not align with local conditions, indicating that some model outputs reflected broader regional data rather than context-specific information.

Although the GPT produced scientifically sound advice, some recommendations were difficult to apply at the homeowner level. One tester pointed out that the degree-day model for Peach Twig Borer control, while technically correct, was "not helpful for a homeowner." Another tester found suggestions for low-chill varieties in Southern Utah unfamiliar in local practice, indicating a need for adjusting region-specific data. These examples indicate the need for further development, such as integrating an external Application Programming Interface (API) and model training on historical spray timelines to address community-oriented uses.

When asked about suitable peach varieties in Southern Utah, the Utah PeachBot returned a comprehensive list that one tester deemed partially consistent with current orchard practices. Several recommended cultivars aligned with local usage, though others were derived from generalized sources (i.e., Utah Farm Bureau). Another tester expressed concerns about the reliability of USDA zone maps in certain Utah regions, where cold snaps periodically exceed average zone temperatures. Consequently, while the GPT's variety recommendations were broadly correct, the feedback draws attention to the necessity of localized revisions, especially in microclimates with atypical temperature fluctuations.

Most comments focused on the accuracy of pest and disease information, especially concerning brown rot and peach tree borers. Testers found the inclusion of organic options (e.g., Bacillus thuringiensis, kaolin clay, neem oil, spinosad) and the precautionary statement regarding pesticide use valuable. However, the model occasionally suggested treatments for pests or diseases that do not commonly appear in arid parts of Utah, such as Peach Leaf Curl. One tester sought a comprehensive spray calendar for Peach Twig Borer, noting that while Utah PeachBot's degree-day framework provided a helpful starting point, it lacked granular scheduling guidelines.

One of the testers found the GPT's irrigation information, covering both newly planted and mature trees, to be accurate. Recommended practices, such as deep watering, mulch application, and adjusting water volume based on local soil properties, aligned closely with established practices for orchard management in Utah. The Extension agents found this GPT feature useful when they needed basic references for tedious inquiries.

Conclusions, Discussion, and Recommendations

This study sought to develop and test a low-cost FM for agricultural extension. OpenAI's ChatGPT creation platform was used to design a custom GPT, Utah PeachBot, for horticultural extension agents who frequently provided advisory services to small-scale peach farmers in Utah. The FM was operationally limited to a pilot application and evaluated by six (6) experts based on the model's completeness, precision, and reliability. The FM was generally reliable, providing sound information on queries related to crop varieties, irrigation requirements, and pests and diseases. However, a common theme from expert testing was the inconsistencies in region-specific results. The testers shared that while the results were usually accurate, they sometimes lacked context applicability. In addition, the testers indicated that some recommendations by the FM were impractical for adoption by farmers due to their nature and scale of production. These findings were consistent with Tzachor et al. (2023) and Ibrahim et al. (2024). These authors recommended an idealized FM for extension services with input from human experts during model development and iterative fine-tuning.

All six testers described Utah PeachBot as a reliable tool for Extension agents seeking readily available, research-based information on peach cultivation. However, the limited adaptability of certain recommendations to specific microclimates or homeowner needs highlights areas where further model development would be beneficial. Testers consistently recommended integrating local apps, APIs, fact sheets, and spray data to improve the contextual relevance of the FM. These findings demonstrate the potential of Utah PeachBot and validate the need for context-specific adjustments and ongoing development. Plans to broaden the scope of Utah PeachBot include regular updates to its instructions, knowledge base documents, scheduled retraining sessions, and ongoing feedback loops. Horticulture agents and growers were invited to provide newly released data on emerging diseases and cultivar performance to support the timely integration of updated knowledge. These efforts are expected to support the model's applicability and relevance for small-scale peach producers in Utah.

Shaikh et al. (2024) provided a technical discussion on the potential of "agricultural foundational models (AFM)" (p. 24). The authors also discussed the emerging field of Reinforcement Learning Large Models (RLLMs) and noted its completely untapped potential in agriculture. While these articles are critical to our understanding of GenAI and FMs in agriculture, many concepts are either in a theoretical phase or an early trial phase. We echo the challenges of adopting AFMs outlined in the literature. First, FMs require a significant amount of high-quality data (Li et al., 2024). Agricultural data is highly location-specific due to the variability in environmental conditions across contexts. The computational cost of an FM increases with the number of parameters in the model. Another challenge relates to distribution shift – the FM will encounter data queries different from the data it was initially trained on due to changing factors (Wiles et al., 2022). Distribution shifts were apparent in Utah PeachBot. Besides environmental and spatial data, agricultural data is also temporal. An FM must be able to account for changes in conditions (e.g., seasonality, climate variability). Distribution shifts can be addressed by fine-tuning the model with updated data or using RLLMs (Shaikh et al., 2024).

Another challenge is data ownership and privacy; FMs can produce outputs using intellectual property without permission (Li et al., 2024). The FM must be fine-tuned and trained to use public data to avoid copyright infringement. Extension services can collaborate with other actors in the innovation system for permission to use copyrighted data. We limited Utah PeachBot FM to Utah State University-owned knowledge resources, which circumvents issues of cost, data, and intellectual property infringement, but also limits the potential utility of the model. Other major challenges exist, such as ethical use, bias, and fairness. While beyond the scope of this study, these challenges are critical to institutional policies governing AI use and must be factored into implementation (Hauer, 2022).

A multimodal FM, such as OpenAI's ChatGPT, requires vast natural resources, computational power, capital infrastructure, and human capacity (Shaikh et al., 2024). A custom GPT benefits from the existing capital of OpenAI – it leverages the GPT-4 model, cloud storage, computational resources, and API of OpenAI to offer a specialized pre-trained model tailored to an organization (OpenAI, 2024). Custom GPTs can use external APIs and be trained and fine-tuned on context-specific data, including knowledge resources and proprietary datasets. It also requires minimal to no coding to develop model parameters and instructions (OpenAI, 2024; Peng et al., 2023). Yet, the environmental concerns surrounding GenAI should be a relevant factor in policy decisions regarding AI adoption.

Agricultural extension leveraged ICTs to strengthen their linkages with farmers, and in turn, digital agriculture transformed farming through effective and efficient knowledge-sharing processes. Custom GPTs offer a low-barrier option for developing countries to explore the potential of FMs in agricultural extension and rural development. Given the unpredictable nature of climate change, extension's evolving role in sustainable rural development, and the complexity of data required to address the evolving needs of small-scale farmers, custom GPTs can serve as a launchpad for GenAI in advisory services. Nevertheless, we recommend limiting a pilot-phase FM to internal or organizational use only – extension agents can experiment with a custom FM while interacting with farmers, thereby providing feedback to administrators for a tailored implementation protocol.

Future research could quantitatively explore the effectiveness of FMs using Likert-type formats and rating scales (e.g., from misleading to accurate ratings to quantify reliability), and classify incoming client questions by intent (e.g., tactical vs. strategic; problem-solving vs. decision-making) to analyze performance by query type. GenAI is considered one of the most significant transformations in computing (Law, 2024). It is now integrated into ICT devices commonly used by extension agents and farmers. The most popular desktop OS in the world, Windows®, is preloaded with CoPilot, and the most widely used mobile OS, Android, benefits from Google AI tools. ChatGPT and Google offer free subscriptions to their FMs with limited, albeit powerful, functionality compared to their paid service. Researchers are encouraged to further experiment with GenAI for agricultural development, and advisory services should seek to ethically integrate FMs in extension.

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