

Agentic Explainable Artificial Intelligence (Agentic XAI) Approach To Explore Better Explanation

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Keywords

Agentic AI; Large language model; Explainable AI; Human-centered AI, Bias-variance trade-off; Knowledge translation, Agricultural decision support

Highlights

- We introduce the novel concept: Agentic XAI
- Agentic XAI seek for improvement in XAI output explanations recursively
- Human experts and LLMs confirmed that Agentic XAI outperforms XAI
- However, excessive iteration declines the performance due to verbosity.
- Explanation simplicity and complexity follows the bias-variance trade-off.

Abstract

Explainable artificial intelligence (XAI) enables data-driven understanding of factor associations with response variables, yet communicating XAI outputs to laypersons remains challenging, hindering trust in AI-based predictions. Large language models (LLMs) have emerged as promising tools for translating technical explanations into accessible narratives, yet the integration of agentic AI, where LLMs operate as autonomous agents through iterative refinement, with XAI remains unexplored. This study proposes an agentic XAI framework combining SHAP-based explainability with multimodal LLM-driven iterative refinement to generate progressively enhanced explanations. As a use case, we tested this framework as an agricultural recommendation system using rice yield data from 26 fields in Japan. The Agentic XAI initially provided a SHAP result and explored how to improve the explanation through additional analysis iteratively across 11 refinement rounds (Rounds 0-10). Explanations were evaluated by human experts (crop scientists) ($n=12$) and LLMs ($n=14$) against seven metrics: Specificity, Clarity, Conciseness, Practicality, Contextual Relevance, Cost Consideration, and Crop Science Credibility. Both evaluator groups confirmed that the framework successfully enhanced recommendation quality with an average score increase of 30-33% from Round 0, peaking at Rounds 3-4. However, excessive refinement showed a substantial drop in recommendation quality, indicating a bias-variance trade-off where early rounds lacked explanation depth (bias) while excessive iteration introduced verbosity and ungrounded abstraction (variance), as revealed by metric-specific analysis. These findings suggest that strategic early stopping (regularization) is needed for optimizing practical utility, challenging assumptions about monotonic improvement and providing evidence-based design principles for agentic XAI systems.

1. Introduction

Explainable artificial intelligence (XAI) has been used as a powerful framework for AI-driven data analysis in science. By quantifying the importance of explanatory variables and uncovering their relationships with target outcomes, XAI allows researchers to move beyond predictive accuracy toward an understanding of factor associations with the response variable, such as feature importance and dependence plots (Ryo, 2022; Molnar, 2020; Lundberg & Lee, 2017; Ribeiro et al., 2016). Yet, it remains challenging to communicate XAI outcomes to laypersons, hindering trust in AI-based predictions (Schiller et al., 2025; Lipton, 2018; Doshi-Velez & Kim, 2017).

Large language models (LLMs) can, on the contrary, foster science communication with laypersons (Galaz et al., 2025). LLMs possess the capacity to transform technical explanations into natural language narratives, generate counterfactual scenarios, and engage in interactive dialogues that align with knowledge structures (De Clercq et al., 2024). LLM-based advisory systems have demonstrated practical viability across applied domains. For instance, an agricultural advisory system serving over 15,000 farmers with approximately 75% success rates in providing actionable guidance (Singh et al., 2024). Evaluations of conversational LLMs in agricultural extension roles show that LLMs can provide high-quality, structured responses that often surpass those of human extension agents in consistency and comprehensiveness, though they require careful grounding in local data and validation protocols to ensure reliability for critical decisions (Ibrahim et al., 2024; Tzachor et al., 2022).

Given the narrative explanation capability, a few studies have tested the combination of LLM and XAI to provide a narrative explanation of data-driven discovery (Bilal et al., 2025). For instance, key predictors found with a SHAP analysis can be explained in plain language. However, no previous study has assessed the potential of XAI-LLM integration with domain experts, making it difficult to understand the extent to which this approach is useful. Moreover, it remains unclear to what extent the AI should provide an explanation from the XAI results. We argue that the approach could generally improve the explanation capability, but there is a trade-off between simplicity and comprehensiveness. A simple explanation of the system is easier to digest for laypersons or domain experts, but it may discard critical information. Meanwhile, an overly comprehensive description may blur important points. Therefore, we hypothesize that there is an optimal level of explanation comprehensiveness. This idea can be regarded as analogous to the bias-variance trade-off in machine learning. The user may receive biased information from a simplistic explanation, while how he/she digests the information can vary if too extensive explanation is given.

To test the hypothesis, this study demonstrates an ‘agentic XAI’ approach. While various definitions are possible, in this study, we define agentic XAI as an AI approach where an agent explores the best possible explanation of modeled patterns through the iterative refinement process of natural language description. Agentic AI is an emerging technique where an (multimodal) LLM operates as an autonomous agent capable of reasoning through multiple steps, retrieving external knowledge, and validating its outputs through feedback loops (Acharya et al., 2025; Hosseini et al., 2025; Sapkota et al., 2025). Recent implementations such as ReAct (Yao et al., 2023) and AutoGen (Wu et al., 2023) have demonstrated the viability of agentic architectures across diverse domains. However, no study has investigated the potential use of agentic AI combined with XAI. Our ambition is to enable smoother knowledge transfer from data science to domain experts and practitioners by providing explanations that are both technically rigorous and practically meaningful.

As a case study, we investigated agricultural systems, where complex interactions between soil properties, meteorological conditions, and management practices create substantial challenges for translating AI outputs into actionable farmer guidance (Holzinger et al., 2022; Gardezi et al., 2023). We generated recommendations through 11 iterative refinement rounds (Rounds 0-10) and employed a hybrid evaluator

design combining human domain experts (crop scientists, n=12) with LLM-as-judge (Zheng et al., 2023) evaluators (n=14) to assess, using seven quality metrics, whether a bias-variance trade-off analogy emerges as refinement progresses and whether overall quality follows an inverted U-shaped pattern.

We demonstrate that the best explanation occurs at intermediate refinement levels rather than through extensive iteration. Excessive refinement produces diminishing or negative returns, with models losing 60-80% of their capabilities within 2-3 cycles due to reward overoptimization and distribution shift (Zhu et al., 2024; Rafailov et al., 2024; Adnan et al., 2025), revealing a bias-variance trade-off analogy critical for trustworthy XAI systems.

2. Materials and methods

2.1 Proposed framework

The proposed agentic XAI framework comprises three interconnected components that enable iterative refinement of agricultural recommendations: (1) XAI analysis to elucidate yield drivers from a tabular dataset (Fig. 1a), (2) multimodal LLM (MLLM)-driven iterative refinement of recommendations for farmers (Fig. 1b), and (3) systematic evaluation across multiple metrics (Fig. 1c). This architecture embodies an agent-like behavior wherein the MLLM progressively enhances its outputs through self-reflection, supplementary analysis generation, and iterative refinement.

All materials for reproducing the agentic XAI workflow are available on Zenodo: <https://doi.org/10.5281/zenodo.17876330> (Yamaguchi, 2025). The repository includes the "Prompts" folder and "PythonCode.ipynb", which chronicles the code generation process from the initial baseline (Round 0) through all refinement stages (Rounds 1-10). Additionally, the "Figures" and "Recommendations" folders contain the complete sequence of visualization outputs and farmer recommendations, documenting the step-by-step expansion of the agent's analytical scope.

The theoretical foundation draws from cybernetic principles of feedback control adapted to knowledge translation (Holzinger et al., 2022), and conceptually applies the ReAct paradigm (Yao et al., 2023) wherein reasoning traces and analytical actions are interleaved to improve outputs. The framework implements a self-reflective mechanism inspired by recent advances in iterative refinement methodologies (Madaan et al., 2023; Wei et al., 2022). At each iteration, the MLLM analyzes its previous outputs, identifies analytical gaps, generates supplementary visualizations and statistical analyses through code generation, and produces enhanced recommendations. This approach leverages the reasoning capabilities demonstrated by chain-of-thought prompting while incorporating domain-specific constraints to maintain practical grounding (Pang et al., 2024).

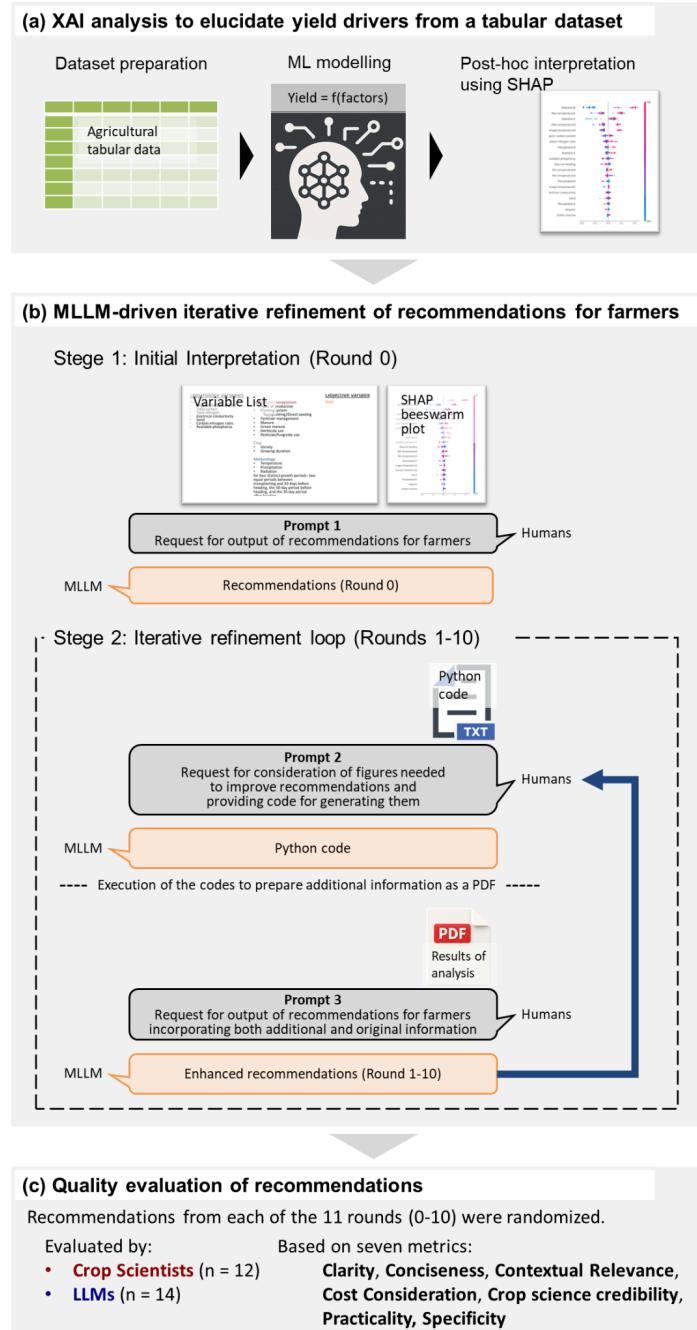


Fig. 1. Framework architecture of agentic explainable AI (XAI). The system integrates machine learning yield prediction with SHAP-based explanation and multimodal large language model (MLLM)-driven iterative refinement. (a) Input preparation proceeds from tabular data preparation, Random Forest modeling to SHAP visualization. (b) The agentic feedback loop enables iterative refinement where the MLLM analyzes XAI outputs, generates supplementary analytical code and visualizations, and produces progressively enhanced farmer recommendations through multiple refinement cycles. (c) Recommendations from all 11 rounds were randomized and evaluated by crop scientists (n=12) and LLMs (n=14) across seven metrics.

2.2 Dataset

We utilized a dataset collected from a Japanese farm field that combined yield data with associated soil properties, rice varieties, cultivation management practices, and meteorological data. The dataset was collected in a single farm operation spanning 26 fields across three years (2021-2023), with four rice varieties. The experiments were conducted in Tomioka-machi, Futaba-gun, Fukushima Prefecture (37.34°N , 141.00°E), covering approximately 9 hectares in total. We used four local rice varieties: Fukunoka (medium-height, used for sake production), Gohyakugawa (very early-ripening, with short stems), Sakurafukuhime (early-maturing, tall with strong stems), and Tennotsubu (medium-height, lodging-resistant).

Yield maps were generated from UAV imagery using a deep learning model (Xception) trained on maturity-stage images with three spectral bands (green, near-infrared, red edge), followed by spatial interpolation using the Inverse Distance Weighting method. The detailed methodology is described in Yamaguchi et al. (2025a). Soil properties were measured annually using a tractor-mounted real-time sensor system with hyperspectral capabilities (Kodaira and Shibusawa, 2013). Meteorological data were obtained from a gridded climatological database provided by the National Agriculture and Food Research Organization (NARO) (Ohno, 2014), with variables averaged across four growth periods: two equal periods between transplanting and 30 days before heading (early/late vegetative stage), the 30-day pre-heading period (reproductive stage), and the 35-day post-heading period (ripening stage).

All variables, including soil properties and yield, were averaged at the field level, resulting in 66 field-year observations across the three-year study period ($n = 66$). This dataset structure reflects typical smallholder farming contexts in East Asia, where field-level variation in soil properties, management practices, and environmental conditions creates complex yield-determining patterns that challenge conventional analytical approaches. The variables used in this study are summarized in Table A.1.

2.3 XAI analysis to elucidate yield drivers from a tabular dataset

To establish the foundation for iterative refinement, we developed a Random Forest model for rice yield prediction from tabular agricultural data and applied SHAP analysis to generate explainability visualizations (Fig. 1a). These initial outputs served as the starting point for the LLM-driven iterative refinement process described in Section 2.4.

2.3.1 Model development and configuration

All yield prediction models were implemented in Python 3.9.13 using scikit-learn 1.5.2, SHAP 0.46.0, NumPy 1.26.4, pandas 2.2.0, and matplotlib 3.8.2. The complete package versions are provided in the supplementary materials to ensure reproducibility.

We employed a Random Forest regressor as the base model due to its robustness, interpretability, and demonstrated effectiveness in agricultural applications (Raharimanana et al., 2023; Yamaguchi et al., 2025b). Model performance was evaluated using leave-one-out cross-validation (LOO-CV) across six hyperparameter configurations, systematically varying the number of estimators (100 or 200) and maximum tree depth (None, 10, or 20): (1) 100 estimators with unlimited depth, (2) 200 estimators with unlimited depth, (3) 100 estimators with max depth of 10, (4) 200 estimators with max depth of 10, (5) 100 estimators with max depth of 20, and (6) 200 estimators with max depth of 20. All models used a fixed random state of 42 as the seed for the pseudorandom number generator to ensure

reproducibility. The optimal configuration was selected based on the R^2 score, and the final ML model was developed with the whole dataset using the optimal configuration.

The optimized Random Forest model, configured with 100 estimators and a maximum depth of 10, achieved an R^2 score of 0.749 in the leave-one-out cross validation setting. R^2 score of the training dataset in the final ML model was 0.962. The gap between training and cross-validation performance suggests potential overfitting, though the cross-validation score indicates adequate predictive capability for generating SHAP-based explanations in this framework.

2.3.2 SHAP-based interpretation

SHAP (TreeExplainer) was employed to generate feature importance scores and interaction effects (Lundberg & Lee, 2017) on the final ML model. This method demonstrates superior performance in agricultural contexts compared to alternative XAI approaches, providing both global and local interpretability while maintaining computational efficiency (Ryo, 2022; Kaler & Kaur, 2025). We analyzed the top 20 most influential features based on mean absolute SHAP values. The primary visualization was a beeswarm plot showing the distribution of SHAP values for each feature, providing insights into both feature importance and directional effects on yield prediction.

SHAP analysis identified management timing variables, meteorological conditions during critical growth phases, and soil nutrient parameters as primary determinants of yield (Fig. S2). This SHAP beeswarm plot served as the input for the subsequent agentic XAI process, wherein the MLLM iteratively analyzed and refined cultivation management recommendations across multiple refinement rounds (Rounds 0-10).

2.4 MLLM-driven iterative refinement of recommendations for farmers

The agentic XAI framework utilizes a Multi-modal Large Language Model (MLLM) to perform an iterative analysis loop (Fig. 1b) that implements principles from recent work on self-refinement and iterative reasoning optimization (Madaan et al., 2023; Kumar et al., 2024). We employed Claude Sonnet 4 (Anthropic) with standard settings: web search disabled, normal response style, and without extended thinking mode. The process is defined by a sequential workflow where the MLLM alternates between interpreting data, generating Python code to extract new statistical evidence, and updating its recommendations based on that evidence.

The workflow consists of an initialization phase followed by a defined number of refinement iterations (Rounds 1-10). The specific inputs and prompts for each stage are detailed below:

Stage 1: Initial Interpretation (Round 0)

- **Input:** The MLLM is provided with the SHAP beeswarm plot image and a list of variables.
- **Prompt 1:** Request for output of recommendations for farmers.
- **Action:** The model generates a baseline textual interpretation and set of recommendations based solely on the visual features of the SHAP plot.

Stage 2: Iterative Refinement Loop (Rounds 1-10)

In each subsequent round, the framework executes a three-step cycle to update the recommendations:

1. Gap Analysis and Python Code Generation:

- **Prompt 2:** Request for consideration of figures needed to improve recommendations and providing code for generating them
- **Action:** The MLLM reviews its previous output and the dataset structure to identify variables that require quantitative verification (e.g., specific correlation coefficients or feature interactions not visible in the initial plot). The model then outputs executable Python code intended to calculate these statistics or generate supplementary plots.

2. Execution and Data Retrieval:

- **Action:** The generated Python code is executed on the tabular dataset. The resulting outputs (e.g., statistical summaries, correlation matrices, or temporal interaction plots) are compiled into a PDF document.

3. Synthesis and Update:

- **Prompt 3:** Request for output of recommendations for farmers incorporating both additional and original information.
- **Action:** The MLLM receives the new PDF document alongside the original SHAP plot. It synthesizes the quantitative results from the PDF with the visual data to rewrite the recommendations.

Context Management: Throughout the process, the conversation history is preserved. This ensures that in Round N, the model generates responses conditional on the accumulated information from Rounds 0 through N-1, allowing the specific details in the recommendations to become more granular as the model accesses more calculated statistics.

2.5 Quality evaluation of recommendations

2.5.1 Evaluation design and protocol

Recognizing the challenges of evaluating agricultural advisory quality, we implemented a multi-evaluator approach using both human experts (crop scientists) and AI systems (LLMs) (Fig. 1c). Twelve crop scientists with specialized agronomic expertise evaluated the recommendations to ensure that domain-specific knowledge was incorporated into the evaluation process, including a nuanced understanding of Japanese farming conditions, practical constraints, and established agronomic principles. These crop scientists were PhD holders in agricultural sciences who are current or former members of the Crop Science Society of Japan. This human expert evaluation was complemented by assessments from 14 LLMs from five major AI providers: OpenAI (ChatGPT 4o, ChatGPT 5.1 Instant, ChatGPT 5.1 Thinking), Anthropic (Claude Sonnet 4, Claude Opus 4.1, Claude Sonnet 4.5), xAI (Grok 3 Fast, Grok 3 Expert, Grok 4.1), DeepSeek (DeepSeek, DeepSeek with DeepThink), and Google (Gemini 2.5 Flash, Gemini 2.5 Pro, Gemini 3.0 Pro). Recent studies demonstrated that properly implemented LLM evaluators can achieve 75-85% agreement with human expert judgments (LLM-as-judge), particularly when using multiple models to mitigate individual biases (Zheng et al., 2023; Liu et al., 2023; Kim et al., 2024a, 2024b).

Each evaluator, including both crop scientists and LLMs, independently evaluated recommendations from all 11 rounds (Round 0-10) based on seven evaluation metrics. Drawing on agricultural decision support system evaluation frameworks that emphasize accessibility, usability, and practical implementation (Zhai et al., 2020), user acceptance and workload considerations (Htun et al., 2022),

and economic value assessment (Helps et al., 2024), we developed the seven evaluation metrics (Table 1), with scores ranging from 1 for very poor to 7 for excellent.

Table 1. Evaluation metrics for assessing recommendation quality.

Metrics	Definition
Clarity	Is the response easy to understand, well-structured, and free from ambiguity? Is the logical flow clear? Is technical terminology explained when necessary? Can farmers grasp the main points without confusion?
Conciseness	Is the response succinct and to the point without unnecessary verbosity? Does it avoid redundant information or excessive repetition while still being complete? Can busy farmers read and understand it quickly during their work breaks?
Contextual Relevance	Does it avoid over-generalization or excessive theoretical discussion that doesn't fit the given background? Does the response align with the actual conditions and context provided in the dataset (location, varieties, field scale, management practices)? Is the advice appropriate for the specific farming scenario described?
Cost Consideration	Does the response address economic factors such as costs, budget requirements, return on investment, or cost-effectiveness? Does it consider the financial constraints that farmers typically face?
Crop Science Credibility	Is the response agronomically sound and reliable from a crop science perspective? Does it reflect established scientific principles in agronomy, plant physiology, soil science, and crop management? Is the information accurate and credible based on current agricultural research and best practices?
Practicality	Does the response offer actionable and feasible advice or solutions that can be realistically implemented? Are the suggestions achievable with typical farm resources, skills, and time constraints?
Specificity	Does the response provide detailed and precise information rather than being vague or general? Does it include specific numbers, measurements, varieties, methods, or step-by-step instructions that farmers can directly reference?

Before the evaluation, crop scientist evaluators received the following background information through written materials and oral explanations in an online meeting, while the LLM received the same information in written form. This background included comprehensive information describing the dataset context (as detailed in Section 2.2) and the 37 input variables categorized into soil properties (7 variables), agricultural management practices (10 variables), and meteorological conditions (20 variables across four growth stages), with yield as the target variable (Table A.1). Evaluators were informed that the descriptions were generated through an iterative refinement process where the LLM auto-regressively analyzed the tabular data and continuously revised its outputs across 11 cycles (Rounds 0-10), with each response containing agronomic insights analyzing relationships between explanatory variables and rice yield, along with practical recommendations for local farmers.

To minimize systematic biases such as position effects and verbosity bias documented in LLM evaluation studies (Ye et al., 2024; Chern et al., 2024), we applied the same evaluation protocol to both crop scientists and LLMs. For each evaluator, the sequence in which the 11 recommendations (Rounds 0-10) were presented was randomized. Each evaluator provided independent assessments without knowledge of other evaluators' scores or the iteration number being evaluated, ensuring blind evaluation.

To ensure unbiased evaluations, all LLM evaluations were conducted in isolated conversation contexts. For ChatGPT, Claude, and Grok models, evaluations were performed in incognito/private mode to prevent any influence from previous conversation history. For DeepSeek and Gemini models, which do not offer an incognito mode, evaluations were conducted in completely new conversation threads with no prior conversation history.

2.5.2 Statistical analyses

After collecting the assessments, we organized the evaluation data separately for crop scientist evaluations ($n = 12$) and LLM evaluations ($n = 14$), treating each evaluator (or repetition) as an independent replicate within its group. For each round (0-10), we computed an overall quality score for each evaluator by averaging the seven evaluation metrics. For each metric and the overall score, we then calculated descriptive statistics across evaluators within each group for each round (mean and standard error of the mean, SEM).

To test whether recommendation quality differed across rounds, we conducted one-way ANOVA for each metric and the overall score. The null hypothesis assumed equal means across rounds, and statistical significance was evaluated at $\alpha = 0.05$.

To assess whether recommendation quality exhibited an inverted U-shaped trajectory across rounds, we fitted a generalized additive model (GAM) relating round number (X) to the round-level mean score (Y):

$$Y = \beta_0 + f(X) + \varepsilon$$

where $f(X)$ represents a smooth function estimated via penalized regression splines with smoothing parameters selected by internal grid search.

Detection of an inverted U-shape was based on the first derivative of the fitted smooth, following derivative-based change detection approaches for GAMs (Simpson, 2018; von Brömssen et al., 2021). The derivative was evaluated by numerical differentiation over a dense grid of round values. We classified a trajectory as inverted U-shaped when all of the following criteria were met: (i) exactly one zero-crossing occurred within the observed range at which the derivative changed sign from positive to negative; (ii) the derivative was positive on average in early rounds and negative on average in later rounds; and (iii) the 95% confidence interval for the derivative excluded zero in both regions, indicating a statistically robust increase followed by a robust decrease. The peak round was defined as the zero-crossing location, and the peak score was obtained from the fitted GAM curve at that round.

In our implementation, 95% confidence intervals for the GAM mean function were computed as pointwise intervals from the fitted penalized spline model, using the estimated coefficient covariance matrix derived from the (penalized) design matrix and the residual variance. Confidence intervals for the first derivative were then approximated by numerically differentiating the lower and upper 95% confidence interval curves for the mean function across the evaluation grid.

Additionally, to evaluate whether the nonlinear GAM provided a better description of the observed trajectories than a simple linear trend, we fitted a linear ordinary least squares regression model as a baseline:

$$Y = \alpha_0 + \alpha_1 X + \varepsilon$$

Model fit was summarized using the coefficient of determination (R^2). To formally compare model performance while accounting for model complexity, we computed Akaike's Information Criterion (AIC) (Akaike, 1973) under a Gaussian error assumption for both the GAM and the linear model:

$$AIC = n[\log(2\pi) + 1 + \log(RSS/n)] + 2k$$

where n denotes the number of observations (rounds), RSS represents the residual sum of squares, and k indicates the number of estimated parameters (effective degrees of freedom for GAM; $k = 2$ for the linear model).

Following the widely cited guidelines of Burnham and Anderson (2002), models with $\Delta AIC < 2$ are considered to have substantial empirical support. We required the GAM to outperform the linear model by at least 2 AIC units ($\Delta AIC = AIC_{\text{Linear}} - AIC_{\text{GAM}} > 2$) to justify adopting the more complex

nonlinear model. The GAM was therefore adopted only when it both satisfied the derivative-based criteria for an inverted U-shaped pattern and demonstrated substantially improved model fit relative to the linear baseline. When this criterion was not met, the linear model was considered sufficient to describe the trend and was used as the reference representation. This comparison-based procedure ensures that nonlinear structure was adopted only when strongly supported by the data, thereby reducing the risk of overfitting and avoiding circular inference regarding peak detection.

All analyses were conducted in Python 3.12.12 within the Google Colab environment. Data processing and statistical analyses were performed using NumPy (v2.0.2), SciPy (v1.16.3), and Pandas (v2.2.2), with visualization implemented in Matplotlib (v3.10.0). Generalized additive models were estimated using pyGAM (v0.12.0).

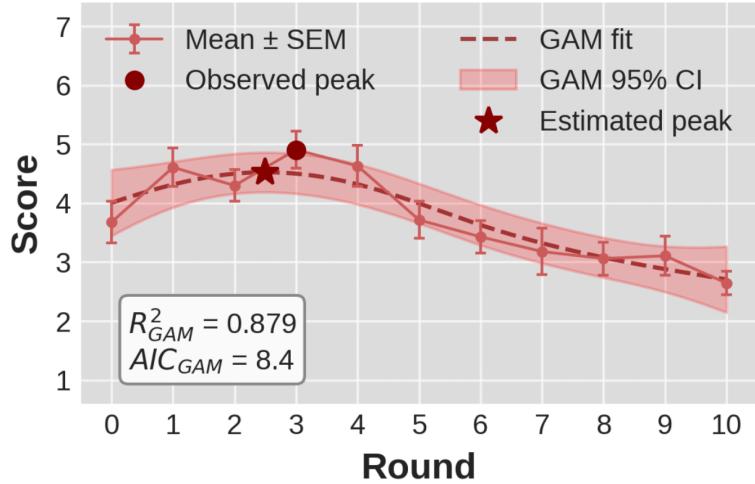
3. Results

3.1 Overall quality dynamics across refinement rounds

The overall average score (mean of seven evaluation metrics) showed a consistent inverted U-shaped pattern across the 11 refinement rounds (Rounds 0-10) in both evaluator groups, with peak performance occurring in early-to-middle iterations followed by substantial deterioration (Fig. 2, Tables B.1 and 2).

One-way ANOVA indicated significant differences across rounds ($p < 0.001$), and GAM analyses detected an inverted U-shaped trajectory for the average score in both crop scientists and LLMs (Table B.2), indicating improvement in the early-to-mid rounds followed by decline. In crop scientist evaluations, the observed average score increased from 3.68 at Round 0 to a maximum of 4.91 at Round 3 ($\Delta = +1.23$), then declined to 2.64 by Round 10 ($\Delta = -2.26$ from the observed peak) (Fig. 2a; Table B.1). The GAM also supported an inverted U-shaped trajectory with an estimated peak at Round 2.50 (estimated peak value 4.523) and better fit than the linear baseline ($\Delta AIC = -9.25$) (Table B.2). In LLM evaluations, the observed average score increased from 4.78 at Round 0 to a maximum of 6.21 at Round 4 ($\Delta = +1.44$), then decreased to 5.18 by Round 10 ($\Delta = -1.03$ from the observed peak) (Fig. 2b; Table B.1). The GAM likewise detected an inverted U-shaped trajectory with an estimated peak at Round 3.53 (estimated peak value 6.028) and strong support relative to the linear model ($\Delta AIC = -13.42$) (Table B.2).

(a) Crop Scientists ($n = 12$)



(b) LLMs ($n = 14$)

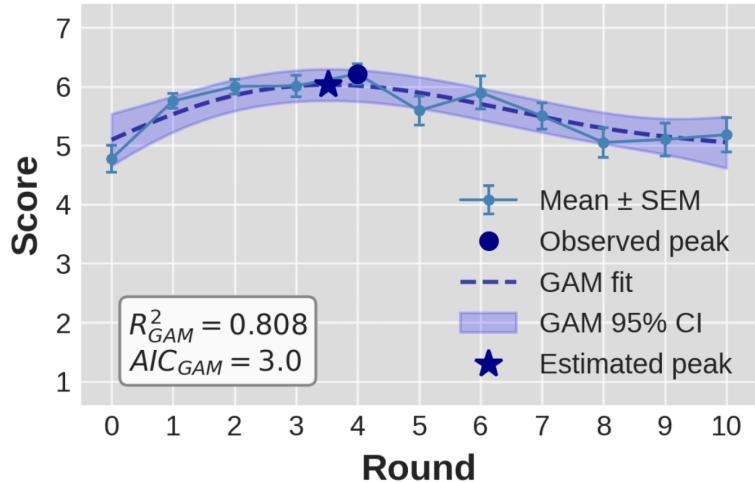


Fig. 2. Average scores (mean of seven evaluation metrics) across rounds for crop scientists (a) and LLMs (b). Points show means and error bars indicate the standard error of the mean (SEM). Dark markers indicate the observed peak (maximum mean value). GAM fit is shown as a dashed curve with shaded 95% prediction intervals; stars mark the estimated peak (derivative zero-crossing).

3.2 Metric-specific performance dynamics

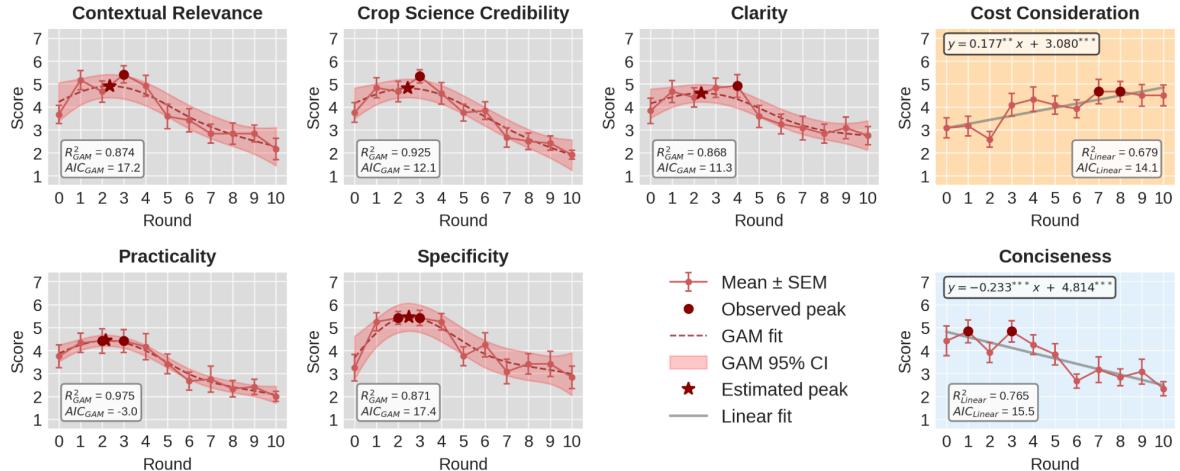
Across metrics, the observed trajectories (Table B.1) and GAM-based trajectory classification (Fig. 3; Table B.2) indicated three distinct patterns: (i) inverted U-shaped dynamics (background gray) for five metrics, (ii) monotonic increases under linear trends (background orange) for Cost Consideration, and (iii) monotonic decreases under linear trends (background blue) for Conciseness.

Five metrics (Specificity, Clarity, Practicality, Contextual Relevance, and Crop Science Credibility) showed inverted U-shaped dynamics in both evaluator groups. These metrics exhibited early-to-mid observed peaks (typically Rounds 2-4) in both crop scientists and LLMs (Table B.1). GAM analyses detected inverted U-shaped patterns for these five metrics in both groups, with improved fit relative to linear baselines ($\Delta AIC > 4$) (Table B.2), supporting an early improvement followed by later decline.

Cost Consideration exhibited a different pattern, characterized by sustained improvement throughout the evaluation period despite late-round observed peaks. For crop scientists, the observed peak occurred at Rounds 7-8 (4.667), with Round 10 maintaining a high value (4.500) (Table B.1). Similarly, LLM evaluations showed the observed peak at Round 9 (6.929), with Round 10 remaining near this peak level (6.714) (Table B.1). Consistent with this sustained late-round performance, GAM criteria did not identify an inverted U-shaped pattern. Instead, linear regression models revealed significant positive slopes for Cost Consideration in both evaluator groups (Fig. 3; Table B.2), confirming monotonic improvement.

In contrast, Conciseness showed early peak performance followed by consistent decline. Crop scientists recorded observed peaks at Rounds 1 and 3 (4.833), which subsequently declined to 2.333 by Round 10 (Table B.1). LLM evaluations showed an even more pronounced pattern, with peak performance occurring at Round 0 (5.929) before declining to 5.143 by Round 10 (Table B.1). In line with these observations, GAM criteria did not detect an inverted U-shaped pattern, and linear regression models demonstrated significant negative slopes for Conciseness in both evaluator groups (Fig. 3; Table B.2), indicating progressive deterioration throughout the evaluation period.

(a) Crop Scientists ($n = 12$)



(b) LLMs ($n = 14$)

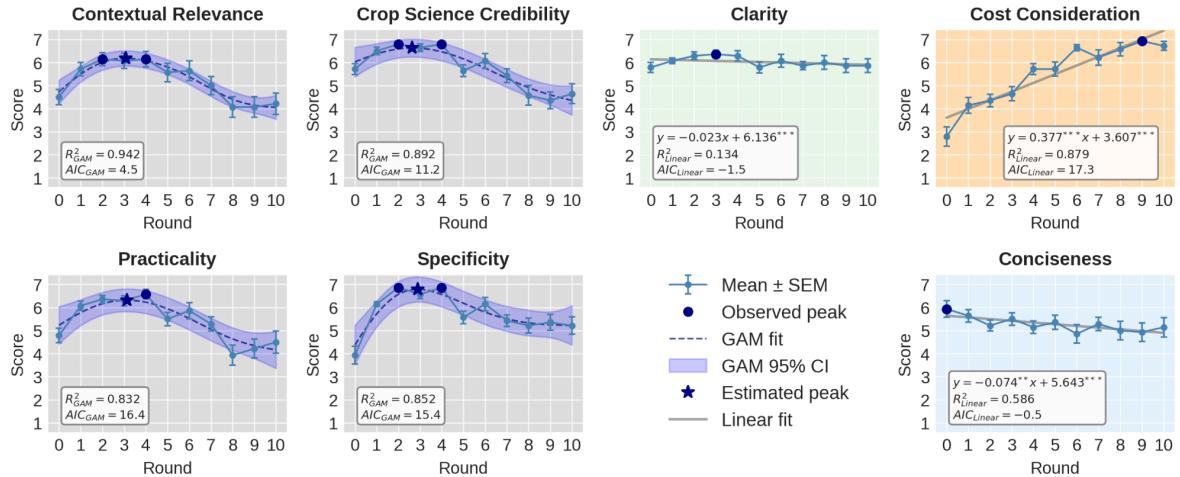


Fig. 3. Individual evaluation metric scores across rounds for crop scientists (a) and LLMs (b). Seven metrics are shown: Clarity, Contextual Relevance, Crop Science Credibility, Practicality, Specificity, Conciseness, and Cost Consideration. Points represent mean scores, and error bars indicate the standard error of the mean (SEM). Dark markers indicate observed peaks (maximum mean values). When an inverted U-shaped relationship was identified using derivative-based criteria and the generalized additive model (GAM) provided a better fit than the linear model ($\Delta AIC > 2$), the GAM fit is displayed as a dashed curve with shaded 95% prediction intervals; stars mark the estimated peak (derivative zero-crossing). Otherwise, linear regression is shown as a solid gray line with the fitted slope and intercept annotated; asterisks indicate statistical significance (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$). Background shading indicates the inferred trend type: gray for inverted U-shaped patterns, green for no trend (no linear slope), orange for monotonic increases (positive linear slope), and blue for monotonic decreases (negative linear slope).

3.3 Progression of analytical complexity across refinement rounds

The agentic XAI framework progressively expanded its analytical scope across 11 refinement rounds (Table 2). Statistical methods and visualization types expanded incrementally, and the accumulated number of visualizations grew from one figure to 93 figures across all rounds.

The analytical focus also shifted. Early rounds (0-3) established mechanistic understanding of yield-limiting factors, management strategies, and environmental interactions. Middle rounds (4-8) introduced economic analysis, field typology classification, and sustainability assessment. Later rounds (9-10) adopted a critical stance, questioning whether increased analytical complexity improved farmer outcomes, while synthesizing recommendations with risk warnings.

Table 2. Progression of analytical methods and visualizations across 11 refinement rounds. New Statistical Methods and New Visualization Types show contents first introduced in each round. Number of Figures indicates figures generated in each round (cumulative total in parentheses).

Round	New Statistical Methods	New Visualization Types	Number of Figures	Analytical Focus
0	Random forest, SHAP	Beeswarm plot	1	Identify key yield-limiting factors using explainable AI
1	Correlation matrix	Bar chart, Heatmap, Line plot, Scatter plot, Violin plot	8 (9)	Compare management strategies and identify critical growth stages for intervention
2	PCA, Q-Q plot, Explained variance	Histogram, Pie chart	17 (26)	Understand weather pattern effects and soil-yield relationships for site-specific management
3	Response curve (binning analysis)	Error bar plot, Text annotation	10 (36)	Quantify environmental factor interactions and provide management timeline
4	Partial dependence, Return on investment	Box plot, Flowchart	9 (45)	Assess economic feasibility and return on investment for precision management adoption
5	K-means Clustering, Response surface methodology, Sensitivity analysis	Contour plot, Roadmap	9 (54)	Identify field typologies and target management strategies by yield potential class
6	Decision tree, Spearman's rank correlation	Filled area plot, Boxed note	7 (61)	Evaluate long-term profitability and sustainability under climate/market uncertainty
7	Kolmogorov-Smirnov test, Polynomial regression	-	10 (71)	Determine critical thresholds for intervention and quantify implementation risks
8	Monte carlo simulation, DBSCAN clustering, Value at risk	Bubble chart	6 (77)	Assess regional transferability and farmer-specific constraints for technology adoption
9	Anderson-Darling test	Radar plot	8 (85)	Evaluate whether increased analytical complexity actually improves farmer outcomes
10	Beta distribution simulation	Stacked bar chart	8 (93)	Synthesize actionable recommendations with clear risk warnings and exit criteria

4. Discussion

4.1 Agentic XAI successfully refined the recommendations in the initial rounds

Our results demonstrate that the proposed agentic XAI framework significantly enhances recommendation quality in early refinement rounds. Both evaluator groups independently identified peak performance at Rounds 3-4, representing improvements of $\Delta = +1.23$ (crop scientists) and $\Delta = +1.44$ (LLMs) over Round 0 (Fig. 2, Table B.1). This trajectory aligns with recent findings in iterative agentic workflows, where multi-turn reasoning loops rapidly converge to optimal solutions before plateauing (Madaan et al., 2023; Zhang et al., 2024).

By leveraging an LLM-driven agentic approach, our framework effectively bridges the persistent "interpretability-usability gap" in XAI applications (Hegselmann et al., 2023; Bilal et al., 2025), synthesizing raw SHAP-based outputs into intelligible narratives that facilitate practical decision-making for farmers (Wang et al., 2024). The convergent validation by both human domain experts and LLM-as-judge evaluators strengthens confidence in these quality improvements, demonstrating that the framework successfully translates technical XAI outputs into actionable guidance.

4.2 The bias-variance trade-off: implications for early stopping

Our results validate the hypothesized bias-variance trade-off analogy in explanation comprehensiveness, suggesting that early stopping is crucial for maintaining quality. The average quality across both evaluator groups follows an inverted U-shaped trajectory as identified by derivative-based GAM criteria, indicating an optimal range in the early-to-mid rounds (Rounds 2-4) before later deterioration (Fig. 2; Tables B.1 and B.2). In this framing, early rounds lack sufficient analytical depth (analogous to bias), while continuing beyond the optimal early stopping point leads to verbosity and abstraction that obscure actionable insights (analogous to variance).

Individual evaluation metrics revealed distinct temporal patterns reflecting different aspects of this trade-off. Five metrics (Contextual Relevance, Crop Science Credibility, Practicality, Specificity, and Clarity) showed early-to-mid observed peaks (within Rounds 2-4) (Table B.1) and were also classified as inverted U-shaped by the GAM-based analyses except for Clarity in LLMs (Table B.2), indicating sensitivity to over-refinement where additional iteration degraded quality through increasing abstraction (Fig. 3). Cost Consideration exhibited continued improvement beyond Round 4, while Conciseness declined monotonically from the earliest rounds (Fig. 3). These divergent patterns demonstrate that different quality metrics exhibit varying sensitivity to the bias-variance trade-off and cannot be simultaneously optimized through simple iteration.

The bias side of this trade-off manifests in early rounds (Rounds 0-2), where recommendations lack sufficient analytical depth. At Round 0, the MLLM generates initial interpretations based solely on the SHAP beeswarm plot without supplementary quantitative analyses, resulting in recommendations that lack the specificity and agronomic detail necessary for actionable farmer guidance. Quality improvements across six metrics (excluding Cost Consideration) from Round 0 to Rounds 2-4 reflect the successful incorporation of additional analytical depth through iterative refinement (Fig. 3; Table 2).

The variance side of the trade-off emerges in later rounds (Round 5 onwards), where continued refinement introduces multiple forms of degradation. Most directly, Conciseness peaked in early

rounds then declined progressively across both evaluator groups, capturing the progressive verbosity that overwhelms laypersons with excessive detail (Fig. 3). Beyond mere length, the MLLM exhibits increasing abstraction and generalization, generating recommendations that are analytically sophisticated (Table 2), but divorced from implementable practices. Cost Consideration's continued improvement through late rounds exemplifies this problem (Fig. 3): since the original dataset lacked economic parameters (Table A.1), the MLLM progressively generated economic reasoning without adequate grounding data. This ungrounded analytical expansion represents precisely the "high variance" phenomenon we hypothesized, elaborate content that lacks empirical foundation. The consistent decline in four metrics (Contextual Relevance, Crop Science Credibility, Practicality, and Specificity) in later rounds across both evaluator groups demonstrates that these practical metrics are particularly vulnerable to this variance-side degradation, losing the concrete specificity that makes recommendations actionable for farmers despite increased analytical sophistication (Fig. 3).

This observation aligns with recent findings on diminishing returns in iterative AI systems, where models lose substantial capabilities within limited refinement cycles due to reward overoptimization and distribution shift (Zhu et al., 2024; Rafailov et al., 2024; Adnan et al., 2025). In our agricultural context, the iterative refinement process appears to optimize for analytical comprehensiveness and economic completeness while inadvertently sacrificing the operational specificity and contextual grounding essential for farmer decision-making. Our results suggest that early stopping strategies (3-4 rounds) can outperform extensive iteration in this context, extending emerging evidence from machine learning research (Snell et al., 2024; Zhu et al., 2024) to knowledge translation applications. This finding suggests that early stopping can be an effective strategy for balancing the competing demands of explanation comprehensiveness in agentic XAI systems.

4.3 Challenges in accountability, transparency, and trust for agentic XAI

While agentic XAI systems demonstrate potential for knowledge translation within the early stopping window, their deployment introduces risks warranting careful consideration beyond optimal iteration counts.

The nature of agentic systems creates accountability challenges and risks generating unfounded analyses when lacking appropriate grounding data. From a principal-agent perspective, the relationship between farmers and agentic systems introduces information asymmetries and potential misalignment between system objectives and farmer interests (Gabison & Xian, 2025), with unclear liability frameworks potentially impeding adoption when agent-generated advice leads to suboptimal outcomes. Our results reveal a critical vulnerability: despite the original dataset lacking economic parameters (Table A.1), the agent increasingly incorporated complex economic reasoning in later rounds (Fig. 3). This pursuit of economic completeness drove the degradation of Crop Science Credibility and Practicality, as the LLM defaulted to abstraction without necessary grounding data, producing recommendations that were analytically enhanced but agronomically detached (Fig. 3). The agential generation and execution of analytical code introduces further vulnerabilities: unintended data manipulation, accumulation of analytical errors across iterations, and propagation of flawed analyses through multiple refinement rounds without external validation (Raza et al., 2025). Our finding that quality deteriorates substantially beyond Round 4 while the system continues generating increasingly complex analyses illustrates this risk. The agential process lacks internal mechanisms to recognize the groundlessness of its own reasoning.

While agentic XAI aims to enhance interpretability, the agential refinement process itself introduces opacity that may reduce rather than enhance trust. The nature creates "black box" challenges where

non-deterministic execution flows and unpredictable behavioral variability hinder accountability and comprehension (Moshkovich et al., 2025). Farmers must trust the original model, its SHAP interpretation, the LLM's self-generated analyses, the code producing those analyses, and the synthesis of multiple information sources. The complexity compounds across iterations, suggesting that even optimal stopping involves substantial trust requirements compared to simpler advisory approaches.

Systematic examination of intermediate outputs by domain experts could help mitigate these opacity concerns by establishing observability into the agentic refinement process (Limonad, 2025; Moshkovich et al., 2025). As shown in this study, archiving agentically generated code and visualizations as documented in the Zenodo repository (Yamaguchi, 2025) enables transparency and expert verification of each iteration's analytical artifacts, helping identify analytical errors and verify agronomic soundness.

4.4 Methodological considerations and limitations

First, this study is based on data from a single crop system (rice) under specific geographical conditions (Fukushima, Japan), which limits generalizability. Different agricultural systems may exhibit distinct patterns of response to iterative refinement, particularly those with different complexity levels, decision-making timescales, or cultural contexts. The framework's performance with perennial crops, livestock systems, or integrated farming approaches remains unexplored. However, the convergent patterns across independent evaluator groups and the theoretical alignment with broader machine learning findings on iterative refinement suggest that the early stopping principle may generalize beyond this specific context.

Second, the implementation of the agentic XAI framework relied on a single generation model (Claude Sonnet 4). Consequently, the observed refinement trajectories may be specific to this model's architecture or training data. Furthermore, while we employed 14 diverse evaluator LLMs to ensure robustness, we must acknowledge the potential for correlated biases within the evaluation process. Since models from the same providers or model families often share training corpora and alignment objectives (e.g., RLHF), they may exhibit similar evaluation tendencies. Therefore, the consistency observed across evaluators should be interpreted with caution, as it may reflect shared underlying artifacts rather than strictly independent validation.

Third, the evaluation is based on recommendation quality assessed at the time of generation, without field validation of implementation outcomes over time. While the quality metrics employed align with established agricultural decision support system evaluation frameworks (Zhai et al., 2020; Htun et al., 2022; Helps et al., 2024), the ultimate test of effectiveness lies in farmer adoption, implementation fidelity, and agricultural outcomes. Future field validation studies examining real-world implementation of recommendations generated at different refinement levels would provide essential validation of our findings and potentially reveal additional criteria of quality not captured in our evaluation framework.

4.5 Future research directions

The generalizability of the bias-variance trade-off pattern and early stopping principle requires validation across diverse agricultural systems and domains beyond agriculture. Different crops, livestock systems, or environmental management contexts may exhibit distinct refinement dynamics

depending on their complexity levels, decision-making timescales, and data availability. Cross-domain validation studies would establish whether the observed early stopping window represents a universal pattern or context-dependent phenomenon. Testing agentic XAI frameworks in medical diagnostics, financial advisory systems, or environmental risk assessment could reveal whether the observed trade-offs constitute a fundamental characteristic of knowledge translation systems or reflect domain-specific constraints. Such systematic validation would provide empirical foundations for establishing evidence-based design principles applicable across diverse applied domains (Holzinger et al., 2022; Wang et al., 2024).

Hybrid human-LLM evaluation approaches integrated with comprehensive observability mechanisms could serve as a promising pathway for building trustworthy agentic XAI systems. Adhering to human-centered AI principles (Holzinger et al., 2022; Shneiderman, 2020) requires meaningful human involvement throughout the evaluation process to ensure systems serve human needs and values. The substantial convergence between human experts and LLMs, with both groups independently identifying similar optimal performance windows, suggests that LLM evaluators could augment limited human expert resources through scalable preliminary assessments. However, maintaining responsible AI principles (Gardezi et al., 2022; Dara et al., 2022) demands determining the appropriate balance of human oversight to ensure domain credibility. Establishing observability through systematic examination of intermediate outputs, including agentically generated code, visualizations, and statistical analyses, ensures analytical validity (Limonad, 2025; Moshkovich et al., 2025) and enables domain experts to identify analytical errors and detect ungrounded reasoning, as demonstrated by the Cost Consideration metric's improvement despite lacking economic parameters. Critically, ultimate validation requires assessment by end users, farmers as laypersons in this context, who judge whether recommendations are truly understandable, actionable, and valuable for practical decision-making (Zhai et al., 2020; Htun et al., 2022; Gardezi et al., 2023). Future research must identify the optimal balance between automated LLM monitoring for efficiency, strategic domain expert validation for credibility, and end-user evaluation for practical utility. This integration of hybrid evaluation across multiple stakeholder levels and observability would enable more accurate identification of genuine quality peaks.

Future agentic XAI systems could overcome the early stopping limitation by incorporating additional grounding data when initial performance peaks are reached. The quality degradation beyond Round 4 observed in this study reflects fundamental constraints imposed by finite information sources. Emerging integration protocols such as Model Context Protocol (MCP) (Anthropic, 2024) or retrieval-augmented generation (RAG) architectures (Lewis et al., 2020; Gao et al., 2023) could enable agents to access real-time agricultural databases, domain-specific literature, or organizational knowledge repositories when initial refinement approaches are exhausted. This iterative expansion of information resources could enable multiple improvement cycles, where each data augmentation phase supports further quality gains before reaching new plateaus, potentially extending the productive refinement window beyond the early stopping limits observed with static information sets.

5. Conclusion

This study demonstrates that agentic XAI systems integrating SHAP-based explainability with multimodal LLM-driven refinement can enhance agricultural recommendations, with optimal performance achieved through strategic early stopping. Both human experts and LLM evaluators independently identified peak quality at Rounds 3-4 (30-33% improvement over baseline), after which continued refinement degraded practical utility through verbosity and ungrounded abstraction despite increasing analytical complexity.

This inverted U-shaped quality trajectory challenges assumptions of monotonic improvement in agentic systems and establishes early stopping as essential for optimizing knowledge translation. Metrics showed distinct temporal patterns: five metrics (Specificity, Clarity, Practicality, Contextual Relevance, Crop Science Credibility) peaked early then declined rapidly; Conciseness decreased nearly monotonically; Cost Consideration improved continuously despite lacking grounding data, exemplifying analytical overreach risks.

These findings yield evidence-based design principles for trustworthy agentic XAI: (1) implement strategic early stopping, (2) integrate hybrid human-LLM evaluation balancing scalability with domain credibility, (3) establish observability protocols enabling expert validation of intermediate outputs, and (4) recognize that quality metrics cannot be simultaneously optimized through iteration alone.

Future research should validate these principles across diverse agricultural systems and broader domains, develop adaptive stopping criteria responsive to real-time quality metrics, and explore integration with external knowledge sources. The convergence between human and LLM evaluations suggests promising pathways for scalable assessment, though ultimate validation requires end-user evaluation by farmers. Understanding fundamental limitations and optimal operational boundaries of agentic AI systems remains critical for responsible deployment serving human needs and values.

CRediT authorship contribution statement

Tomoaki Yamaguchi: Conceptualization, Funding acquisition, Investigation, Methodology, Software, Resources, Validation, Visualization, Writing - original draft, Writing - review & editing. **Yutong Zhou:** Supervision, Writing - review & editing. **Masahiro Ryo:** Conceptualization, Funding acquisition, Investigation, Project administration, Validation, Writing - review & editing. **Keisuke Katsura:** Conceptualization, Funding acquisition, Investigation, Project administration, Supervision, Validation, Writing - review & editing.

Acknowledgments

This work was commissioned by MAFF “Commissioned projects for promotion of strategic international joint research (Joint research with Germany) JPJ008837.”

We express our sincere gratitude to the crop scientists who generously provided their time and expertise to evaluate the AI-generated recommendations in this study.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no competing financial interests or personal relationships that may have influenced the work reported in this study.

During the preparation of this work, the authors used Claude Sonnet 4/Sonnet 4.5/Opus 4 (Anthropic, United States) in order to assist with manuscript proofreading and literature organization. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

Appendix A. Explanatory variables

Table A.1. Descriptions of all 37 explanatory variables used in the XAI analysis.

Category	Variable	Description
Soil properties	Organic matter content	
	Total carbon	
	Total nitrogen	
	Electrical conductivity	
	Sand	
	Carbon-nitrogen ratio	
	Available phosphorus	
Agricultural management practices	Variety	Gohyakugawa (0), Tennotsubu (1), Fukunoka (2), Sakurafukuhime (3)
	Days to heading	Number of days from transplanting to heading
	Planting system	Direct seeding (0) or transplanting (1)
	Organic	Non-organic farming (0) or organic farming (1)
	Green manure	No application (0) or application (1)
	Manure	No application (0) or application (1)
	Soil amendments	No application (0) or application (1)
	Chemical herbicide	No application (0) or application (1)
	Chemical pesticide and fungicide	No application (0) or application (1)
	Years of production	Cumulative years of rice production in the field
Meteorological conditions	Average temperature1	Mean temperature for early vegetative stage
	Average temperature2	Mean temperature for late vegetative stage
	Average temperature3	Mean temperature for reproductive stage
	Average temperature4	Mean temperature for ripening stage
	Max temperature1	Maximum temperature for early vegetative stage
	Max temperature2	Maximum temperature for late vegetative stage
	Max temperature3	Maximum temperature for reproductive stage
	Max temperature4	Maximum temperature for ripening stage
	Min temperature1	Minimum temperature for early vegetative stage
	Min temperature2	Minimum temperature for late vegetative stage
	Min temperature3	Minimum temperature for reproductive stage
	Min temperature4	Minimum temperature for ripening stage
	Precipitation1	Precipitation for early vegetative stage
	Precipitation2	Precipitation for late vegetative stage
	Precipitation3	Precipitation for reproductive stage
	Precipitation4	Precipitation for ripening stage
	Radiation1	Mean solar radiation for early vegetative stage
	Radiation2	Mean solar radiation for late vegetative stage
	Radiation3	Mean solar radiation for reproductive stage
	Radiation4	Mean solar radiation for ripening stage

Appendix B. Statistical summary of evaluation metrics across refinement rounds

Table B.1. Summary of observed scores of evaluation metrics across iterative refinement rounds in crop scientists and LLMs. Mean scores for each metric are shown for Round 0 (initial response), peak performance round(s), and Round 10 (final iteration). Δ Peak vs Round0 indicates the improvement from initial to peak performance. Δ Round10 vs Peak indicates the change from peak to final round.

Evaluator Group	Metric	Round 0	Peak Rounds	Peak	Round 10	Δ Peak vs Round0	Δ Round10 vs Peak
Crop Scientists	Average	3.679	3	4.905	2.643	1.226	-2.262
	Clarity	3.833	4	4.917	2.750	1.083	-2.167
	Conciseness	4.417	1, 3	4.833	2.333	0.417	-2.500
	Contextual Relevance	3.667	3	5.417	2.167	1.750	-3.250
	Cost Consideration	3.083	7, 8	4.667	4.500	1.583	-0.167
	Crop Science Credibility	3.750	3	5.333	1.917	1.583	-3.417
	Practicality	3.750	2, 3	4.417	2.000	0.667	-2.417
	Specificity	3.250	2, 3	5.417	2.833	2.167	-2.583
	Average	4.776	4	6.214	5.184	1.439	-1.031
LLMs	Clarity	5.786	3	6.357	5.857	0.571	-0.500
	Conciseness	5.929	0	5.929	5.143	0.000	-0.786
	Contextual Relevance	4.500	2, 4	6.143	4.214	1.643	-1.929
	Cost Consideration	2.786	9	6.929	6.714	4.143	-0.214
	Crop Science Credibility	5.714	2, 4	6.786	4.643	1.071	-2.143
	Practicality	4.786	4	6.571	4.500	1.786	-2.071
	Specificity	3.929	2, 4	6.857	5.214	2.929	-1.643

Table B.2. Summary of statistical analyses for evaluation metrics across iterative refinement rounds in crop scientists and LLMs. One-way ANOVA tests whether mean scores differ across rounds. Non-linear trends were assessed using generalized additive models (GAMs). Inverted U-shaped patterns were identified based on derivative-based criteria of the GAM fit (a single change from increasing to decreasing). Model fit was compared with a linear baseline using $\Delta\text{AIC} = \text{AIC}_{\text{Linear}} - \text{AIC}_{\text{GAM}}$. When an inverted U-shape was detected, Peak Round and Peak Value indicate the estimated peak location and score. Significance markers: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Evaluator Group	Metric	ANOVA p-value	Inverted-U detected	ΔAIC	Peak Round	Peak Value
Crop Scientists	Average	0.000***	Yes	9.25	2.50	4.523
	Clarity	0.001**	Yes	7.90	2.35	4.596
	Conciseness	0.000***	No	0.00	-	-
	Contextual Relevance	0.000***	Yes	8.22	2.35	4.907
	Cost Consideration	0.009**	No	0.01	-	-
	Crop Science Credibility	0.000***	Yes	12.06	2.45	4.806
	Practicality	0.000***	Yes	17.95	2.17	4.430
	Specificity	0.000***	Yes	12.01	2.50	5.447
	Average	0.000***	Yes	13.42	3.53	6.028
LLMs	Clarity	0.601	No	5.42	-	-
	Conciseness	0.525	No	1.65	-	-
	Contextual Relevance	0.000***	Yes	21.16	3.07	6.177
	Cost Consideration	0.000***	No	8.85	-	-
	Crop Science Credibility	0.000***	Yes	10.27	2.64	6.625
	Practicality	0.000***	Yes	10.73	3.12	6.311
	Specificity	0.000***	Yes	15.51	2.89	6.780

Appendix C. Agentic XAI outputs and prompts

All materials documenting the agentic XAI implementation were deposited in Zenodo: <https://doi.org/10.5281/zenodo.17876330> (Yamaguchi, 2025). The repository contains the prompts controlling the agentic workflow, and for each refinement round (Rounds 0–10), the Python code agentically generated, the resulting visualization outputs, and the textual recommendations produced for farmers. This structure enables full transparency and reproducibility of the iterative refinement process from initial explainability analysis to final recommendations.

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