

Human-AI Collaboration in Agricultural E-commerce Live Streaming: A Task Allocation Framework

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Abstract: Agricultural e-commerce live streaming requires sellers to provide timely and accurate product information while using live demonstrations and interaction to address questions about quality, origin, and after-sales responsibility. Generative AI can help organize information, draft scripts, and answer routine questions, but it cannot independently resolve every issue that calls for on-site verification or an accountable response. Taking specific tasks before, during, and after a livestream as the unit of analysis, this conceptual paper develops a two-dimensional framework based on task codifiability and demands for trust and accountability. Their intersection distinguishes four types of work: tasks that AI can perform independently, tasks for which AI provides support, tasks requiring joint human-AI execution, and tasks led by a human streamer. In practice, these tasks are organized into three operating arrangements: AI-led, collaborative, and human-led live streaming. The framework offers a basis for analyzing how work may be divided between AI and human streamers in agricultural commerce. Its practical value remains to be tested in actual livestream settings.

Keywords: Agricultural livestream e-commerce; generative AI; AI streamers; human-AI collaboration; task allocation.

1. Introduction

Live streaming allows agricultural sellers to show where products are grown, what they look like, and how they are handled. Consumers can also ask questions before placing an order. For fresh produce, maturity, taste, and condition may vary across batches and change with time and transport. A static product page cannot readily convey all of these differences. Research on agricultural live streaming associates streamer, product, and setting cues with consumer engagement and value co-creation (Ning et al., 2025). The informational and interactive value of live streaming can also help build trust in the seller (Wongkitrungrueng & Assarut, 2020).

Farmers, cooperatives, and small agricultural firms often rely on a few people to check product information, prepare content, repeat product explanations, and respond to comments. Seasonal and batch-level changes in fresh produce require frequent updates. Generative AI and AI streamers can assist with scriptwriting, information retrieval, routine questions, and repeated announcements, potentially easing pressure on content production and staffing. Yet not every exchange can be handled through a prepared script. When a viewer asks about the maturity of the batch on sale, requests a demonstration of packaging, or reports damaged goods, the seller must consider on-site evidence, the circumstances of the case, and after-sales responsibility. A fluent automated answer alone may do little to resolve the concern.

Studies comparing AI and human streamers suggest that their relative effectiveness varies by product type, style of interaction, and time (Yuan et al., 2025; Yan et al., 2025; Liu et al., 2025). Most compare streamer types or interaction effects, however, rather than asking how the different tasks within one livestream should be assigned, jointly performed, or handed over when an exception arises. This paper therefore asks how agricultural sellers can allocate particular live streaming tasks between AI and human streamers and adjust that allocation as the session unfolds. It is a conceptual

analysis; the proposed categories are analytical inferences drawn from prior research, not empirically established optimal assignments.

2. Theoretical Background and Unit of Analysis

2.1. The Tasks Involved in Agricultural live streaming

Agricultural live streaming involves more than a streamer speaking on camera. Before a session, sellers verify product and batch information, prepare explanations, and plan demonstrations. During the session, they present products, answer questions, monitor comments, and address unexpected issues. Afterwards, they review inquiries, complaints, and sales data. Zhang et al. (2022) likewise describe the multiple roles performed by e-commerce streamers. Asking only whether AI can replace a human streamer therefore tells us little about how these activities should be divided. This paper treats the individual tasks involved in live streaming as its unit of analysis and examines which parts of each task are suited to AI or to a human.

Such a task-level view is especially useful for agricultural products. Prices and delivery areas can usually be explained repeatedly using updated database records. Questions about the maturity of the current batch, damage in transit, or the authenticity of an origin claim may instead require inspection of the goods, the order, or the production site. Livestream interaction also extends beyond product information: streamers adapt their explanations and responses to viewers' questions. Luo et al. (2024) find that informative and affective topics have different effects on user engagement. Thus, even within a single session, tasks differ in their requirements for verification, situated judgment, and interaction. The division of work between AI and humans should reflect those differences.

2.2. Human–AI Complementarity and Levels of Automation

Research on human–AI complementarity suggests assigning parts of a process according to their requirements rather than assuming that one party should perform the entire job (Jarrahi, 2018). In a livestream, AI can quickly organize verified product records, group recurring questions, and draft alternative responses. A human can determine whether those records apply to the batch being sold, demonstrate the product, and judge how to handle quality claims or disputes. Such complementarity depends on traceable sources and a clear allocation of responsibility.

Raisch and Krakowski (2021) argue that using AI to substitute for some work and using it to assist people are interrelated choices. If AI handles routine questions, a human streamer can spend more time on difficult ones. If AI handles all interaction, however, the streamer may have fewer opportunities to notice emerging problems. Parasuraman et al. (2000) distinguish among automation of information acquisition, information analysis, decision selection, and action implementation. Consider a viewer asking how long a product can be stored. AI might retrieve verified information for the human streamer to check and convey, or it might answer the viewer directly. The latter requires the system to confirm that the information applies to the batch on sale and to refer uncertain cases to a human. The distinction lies in the authority assigned to AI at different stages of the task, even when both approaches use the same source material.

Research on live streaming and trust adds a further consideration. Consumers assess not only the speed of a response but also the credibility of the product and seller (Wongkitrungrueng & Assarut, 2020). Task allocation must therefore account for both whether information and acceptable outputs can be specified and checked in advance, and whether the response requires evidence from an identifiable, accountable seller. These considerations inform the two dimensions developed below.

3. A Two-Dimensional Framework for Task Allocation

3.1. Defining the Two Dimensions

The first dimension, task codifiability, concerns the extent to which the information required, the rules for handling it, and an acceptable result can be specified and checked in advance. Questions about price, inventory, and discounts can generally be answered from current records. Comparing the taste of fruit from the batch on sale, or investigating a complaint about a particular order, is harder to prescribe beforehand. Codifiability does not mean simplicity. It concerns whether the information source is clear, the procedure is stable, and the answer can be verified. The levels-of-automation framework helps distinguish the authority AI may hold in retrieving information, assessing it, and delivering a response (Parasuraman et al., 2000).

The second dimension, demands for trust and accountability, concerns the extent to which completing a task requires on-site evidence, context-sensitive communication, or a clearly accountable seller to explain and remedy a problem. Cutting open a fruit from the current batch in an orchard may be a simple act, but viewers need to know that it represents what is being sold and who stands behind the demonstration. By contrast, summarizing thousands of comments can be computationally demanding yet remain a backstage activity whose results a human reviews before use. Studies of livestream trust and agricultural livestream settings indicate that seller credibility and setting cues matter to consumer engagement (Wongkitrungrueng & Assarut, 2020; Ning et al., 2025). Trust and accountability demands cannot therefore be inferred solely from a task’s difficulty or frequency.

The dimensions address two distinct questions: can the basis for handling a task and its expected result be specified in advance and verified afterwards, and does the outward-facing response call for evidence or responsibility from a human seller? Their combination is an analytical synthesis developed for agricultural live streaming, rather than a scale or typology adopted unchanged from earlier work. A task’s position may vary with the product, batch, or level of dispute.

Table 1. Dimensions and criteria for assessing live streaming tasks

Dimension	Assessment question	Illustrative contrast
Task codifiability	Can the information, rules, and acceptable outcome be specified and verified in advance?	High: explaining a discount from an approved price list. Low: assessing an unusual quality concern raised during the session.
Trust and accountability demands	Does the task require on-site evidence, context-sensitive response, or an identifiable party who is accountable?	High: showing the current batch and addressing a quality dispute. Low: announcing the start time of a session.

3.2. Four Types of Tasks and Their Allocation

Crossing the two dimensions yields four task types. The classification concerns the conditions of a task, not a blanket rule that a particular product must be sold by a particular kind of streamer. The first type combines high codifiability with low trust and accountability demands. Examples include verified prices, stock levels, discount rules, and general delivery information. AI can deliver these messages from an

updated knowledge base, while a human reviews the rules and handles questions outside their scope.

The second type combines lower codifiability with relatively low trust and accountability demands. These are often backstage tasks, such as generating alternative scripts, identifying recurring themes in comments, and organizing material for post-session review. AI can broaden the set of options; a human selects what fits the product and the actual situation. Here, “AI assistance” describes support within a

task, not a separate category of on-screen streamer.

The third type is relatively codifiable but carries high trust and accountability demands. Certificate details, batch records, and after-sales policies may be available for verification. Yet a viewer who questions quality, asks whether a certificate covers the current batch, or seeks compensation for damage needs an explanation tied to the product or order at issue. AI can retrieve records and flag relevant terms; a human checks them, presents the evidence, and provides the final response.

The fourth type combines low codifiability with high trust

and accountability demands. It includes responding to a challenge to a product's stated origin, demonstrating an unexpected feature of the current batch, and handling an emotionally charged complaint while the facts are still uncertain. A human should lead the investigation, demonstration, and conversation. AI may organize records and prompt follow-up questions backstage. These assignments are proposed matches between task characteristics and the two parties' roles. Whether they outperform other arrangements remains an empirical question.

Table 2. Task types and their place in three operating arrangements

Codifiability	Trust and accountability	Example	Division of work	Operating arrangement
High	Low	Price announcements; routine delivery questions	AI responds under approved rules; a human supervises exceptions.	AI-led
Low	Low	Script options; comment summaries	AI proposes alternatives; a human selects them, usually backstage.	AI assistance
High	High	Batch and certificate explanations; standard after-sales disputes	AI retrieves records; a human verifies and explains them.	Collaborative
Low	High	Live demonstrations; unusual quality disputes	A human investigates and responds; AI assists backstage.	Human-led

4. From Task Allocation to Operating Arrangements

The four types in Table 2 describe individual tasks. An operating arrangement describes who speaks to viewers, who decides on the final response, and who takes over when an exception arises during a segment of a livestream. There are three arrangements because AI assistance with backstage work is usually embedded in a human-led or collaborative session rather than constituting a distinct type of AI-assisted streamer. An AI-led arrangement fits segments dominated by routine tasks; a collaborative arrangement fits tasks for which AI can prepare information but a human must interpret it for viewers; and a human-led arrangement fits segments requiring on-site proof or complex communication. A session may move among all three.

4.1. AI-Led Arrangement

In an AI-led arrangement, an AI streamer or automated response system delivers repeated explanations and handles routine questions. A human maintains product records, reviews scripts, and takes over exceptions. This arrangement is most plausible when specifications are relatively stable, information has been checked, and few questions carry substantial risk. Yuan et al. (2025) show that the relative performance of AI and human streamers depends on consumption context and changes over time. The ability to broadcast continuously therefore does not, by itself, justify assigning every task in a session to AI.

AI-led delivery requires clear limits on the information the system may use. Prices, stock, origin claims, certificates, and delivery promises should correspond to records for the batch on sale; the system should not fill gaps by inventing facts. Viewers should be told when the visible streamer is AI-generated. The seller should also specify when a human takes

over, such as when product records conflict, a viewer requests a live inspection, the same quality concern persists, or a complaint involves compensation.

4.2. Collaborative Arrangement

Collaboration is appropriate when AI can assemble relevant material but a human must interpret it and decide what to say. If a viewer asks about pesticide-residue testing, for example, AI could retrieve the report for the relevant batch and identify its date. The human streamer would confirm that the report covers the product on sale, explain what the test does and does not establish, show the appropriate label, and answer further questions. If the report concerns another batch, the seller should say so rather than presenting it as proof for the current one.

AI can also summarize comments backstage, alerting the streamer to recurring concerns and answers that still lack evidence. Liu et al. (2025) find that product-focused and social interactions by virtual streamers affect purchase intention through different mechanisms. That finding suggests that information provision and relational communication should be designed separately; it does not show that AI should handle emotionally sensitive exchanges in agricultural livestreams on its own. Effective collaboration requires the human to see the sources, conversational context, and AI suggestions, and to be able to revise or reject them.

4.3. Human-Led Arrangement

When existing records cannot adequately establish product quality, or viewers specifically question origin, demonstrations, or after-sales responsibility, a human should lead the visible interaction and make the final judgment. The streamer can show the goods, packaging, or production setting in response to viewers' questions, and may invite a producer familiar with the batch to explain it. AI can organize

questions, retrieve records, and keep track of follow-up commitments, but it should not fabricate first-person accounts of growing, testing, or observing the product.

If goods arrive spoiled, the wrong product is delivered, or a quality dispute arises, a human must investigate the order, batch, and delivery history and explain both what can be established and what will happen next. The work involves fact-checking as well as repairing the relationship with the buyer. Yan et al. (2025) find that the relative effects of virtual and human streamers vary by product type. This does not imply that every agricultural product requires a human-led stream; the relevant decision depends on the product and the task.

4.4. Handoffs as Tasks Change During a Livestream

The three arrangements are based on task characteristics, but the demands of a particular task can change during a session. A viewer's question about expected delivery time can be answered by AI using verified rules. If the viewer then reports receiving damaged produce and asks why it happened, the exchange becomes a case requiring investigation of an order, the delivery process, and an appropriate remedy. The broad topic is still delivery, but the task now requires case-specific judgment and an accountable response.

Task allocation should therefore respond to new information. A human should take over when existing records do not answer a question, product information conflicts with what can be observed, or a viewer disputes quality and asks to see the goods. AI can pass along the question, the sources it used, and any answers already given, allowing the human to understand the case without asking the viewer to start again. Once the issue has been resolved and the relevant information verified, routine questions governed by clear rules may again be handled by AI.

Such handoffs follow the same framework used for the initial allocation. The seller reassesses how readily the current task can be verified and how much on-site evidence or accountable explanation it requires, then adjusts the division of work accordingly.

5. Conditions for Implementation and Evaluation

5.1. Task Inventory and Product Records

Sellers can map the work involved in preparing a session, presenting products, answering viewers, handling after-sales issues, and reviewing performance. For each task, they should record the information needed, how readily it can be verified, the consequences of an incorrect answer, and the person responsible. Allocation should be revisited for each product and session. Packaged grain generally has more stable specifications, whereas fresh produce may require renewed checks because batches, storage times, and transport conditions vary. A task inventory can inform staffing, the use of AI streamers, and the conditions for a handoff.

Sellers also need product records with identifiable sources and update dates. These may cover the product name, variety, grade, batch, harvest or production date, inventory, storage and delivery conditions, the scope of any certificate, and promotional terms. If a streamer notices that a record does not match the product, the related automated answer should be suspended until the information has been checked and corrected. Viewers' questions and AI-generated text can

prompt an investigation; neither is, by itself, evidence about the product.

5.2. Responsibility for Verification and Handoffs

The seller should specify who approves product records, who can revise AI-generated scripts, who handles quality disputes, and who is accountable for promises made to buyers. If an AI-generated answer invokes an unverified claim about quality, certification, or health, the system should refer the question to a human. The seller should verify the supporting information before responding publicly. Viewers should be able to identify an AI streamer and recognize when a human has taken over. For consequential disputes, the seller should retain the sources consulted, AI suggestions, human revisions, and final resolution so that the exchange can be reviewed later.

5.3. Evaluating Outcomes at the Task Level

Total sales for a livestream cannot show whether the division of work was appropriate across different tasks. Sellers can assess the accuracy and response time of routine answers. For quality disputes, they can examine the evidence used, time to resolution after a handoff, and recurrence of complaints. Consumer feedback can indicate changes in trust in the product and seller, while work records can show the burden on human streamers. Comparisons across arrangements should account for product category, time of broadcast, and differences in the audience. Sellers should also examine whether incorrect answers are corrected promptly and whether human streamers retain the product knowledge and skills needed to handle exceptions.

6. Discussion and Future Research

The paper's contribution is to recast the choice between AI and human streamers as a set of identifiable decisions about tasks. Even where AI retrieves the same source material, whether it should address viewers directly depends on the need for on-site proof and an accountable explanation. The four task types and three operating arrangements refer to different levels of analysis: the former describe particular pieces of work, while the latter organize a segment of a livestream. This distinction helps explain how AI announcements, live demonstrations, and human handling of disputes can coexist within one session.

The framework also has limits. Existing studies establish the relevance of streamer and product types, interaction styles, and trust, but do not demonstrate that these four task types or their proposed arrangements are optimal. The two dimensions need operational measures, and their boundaries may differ by product category. Whether a timely handoff improves the consumer experience also requires testing. Future studies could compare direct AI answers, AI suggestions checked by a human, and direct human answers for similar products under comparable livestream conditions, recording accuracy, trust, purchase behavior, and after-sales outcomes. Observation and interviews could further examine how farmers, cooperatives, and agricultural firms with different staffing and data resources manage handoffs.

7. Conclusion

The allocation of work between AI and human streamers in agricultural livestream commerce should begin with specific tasks. AI can take on more of the execution when a task can

be repeated using verified information and raises few substantial issues of trust or responsibility. It is better suited to backstage support when the work involves organizing complex material but a human must select how to use it. A human should participate or lead when a task calls for on-site proof, contextual explanation, or responsibility for a remedy. The two-dimensional framework and three operating arrangements provide a way to analyze these choices. Their effectiveness depends on the quality of product records, human capacity to verify them, and the design of handoffs, and remains to be tested in live settings.

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