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Article Review

Utilizing ChatGPT as a Large Language Model for Qualitative Decision Tree Modeling: A Proof-of-Concept for Strengthening Food Security in Indonesia

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ABSTRACT. This study explores the use of Artificial Intelligence, specifically ChatGPT as a large language model, in constructing a qualitative decision tree to support food security analysis in Indonesia. Framed within the FAO's four-pillar approach—availability, access, utilization, and stability—the research adopts a methodological proof-of-concept design and does not rely on primary or secondary empirical datasets. Instead, the analysis is based on AI-generated reasoning derived from structured prompts, which are systematically organized into a conceptual decision tree framework. Validation is conducted through interpretative comparison with established theoretical frameworks and national policy documents, rather than empirical testing or expert elicitation. The resulting model provides a structured representation of strategic pathways and potential policy options, highlighting the advantages of AI-assisted modeling in terms of speed, scalability, and integrative synthesis of knowledge. However, the model remains qualitative and exploratory, with limitations related to contextual specificity, potential bias, and the absence of real-time data. The findings suggest that AI can function as a complementary analytical tool for structuring policy-relevant insights, although its application requires careful validation and should not be interpreted as evidence of policy effectiveness.

INTRODUCTION

Food security remains a critical and strategic priority for Indonesia, particularly given its large population and the complexity of its agribusiness system. Ensuring stable access to safe, nutritious, and affordable food is not only an agricultural concern but also a broader socio-economic and political issue. In the context of agribusiness, food security depends on the performance of interconnected subsystems, including production, distribution, processing, and consumption. Disruptions in any part of this system—whether due to climate shocks, market instability, or logistical constraints—can affect the availability, accessibility, and affordability of food. Therefore, strengthening food security requires integrated and adaptive decision-making across the entire agribusiness value chain, involving farmers, supply chain actors, local governments, and national food institutions.

This study adopts the Food and Agriculture Organization (FAO) framework as its conceptual foundation, which defines food security through four dimensions: availability, access, utilization, and stability. These pillars provide a comprehensive lens for analyzing agribusiness systems, linking farm-level production to market access, nutritional outcomes, and long-term resilience. In practice, however, designing effective food security policies remains challenging due to fragmented data, complex interdependencies, and rapidly changing conditions. Conventional data collection and analysis are often time-consuming and may not adequately support timely policy responses, particularly in dynamic or crisis situations ([FAO] Food and Agriculuture Organization, 2021; Adamchick & Perez, 2020).

Recent advances in Artificial Intelligence (AI), particularly large language models (LLMs) such as ChatGPT, offer new opportunities for supporting policy analysis and decision-making. Existing literature suggests that AI can assist in synthesizing diverse knowledge sources, generating policy scenarios, and supporting decision-support systems. However, most applications of AI in policy contexts rely on empirical datasets, hybrid human–machine systems, or predictive modeling approaches. Similarly, decision tree analysis in food security has traditionally been applied using quantitative data to model risks, classify outcomes, or optimize decisions. These approaches, while valuable, often require extensive datasets and technical resources, limiting their applicability in data-scarce or rapidly evolving contexts (Arora et al., 2025; Machefer et al., 2025; Zaman et al., 2023).

Despite these developments, limited research has explored the use of AI-generated reasoning as a standalone input for constructing conceptual decision-making frameworks. Existing studies rarely address how AI can be systematically used to structure qualitative decision trees, nor do they sufficiently discuss issues of transparency, replicability, and methodological rigor in AI-assisted policy modeling. This gap is particularly relevant in agribusiness systems, where decision-making involves multiple actors, trade-offs, and uncertainties that are not easily captured through purely quantitative approaches (Cao et al., 2025; Machefer et al., 2025; Wang et al., 2025).

In response, this study proposes a methodological proof-of-concept by utilizing ChatGPT to construct a qualitative decision tree for strengthening Indonesia's food security. The decision tree is used to map strategic pathways across the agribusiness system, linking production, distribution, and consumption-related interventions to potential outcomes. By structuring AI-generated insights into a hierarchical decision model, the study aims to provide a transparent and interpretable framework that can support policy exploration and discussion. Importantly, the model is conceptual and exploratory, rather than predictive or data-driven (Allahyari et al., 2025; Pandey & Mishra, 2024; Wang et al., 2025).

The urgencies and objectives of this research are threefold. First, to demonstrate the feasibility of using ChatGPT to generate a qualitative decision tree in the context of food security policy without relying on conventional datasets. Second, to assess the plausibility of the resulting decision pathways through theoretical and policy-based validation. Third, to document the methodological process, including prompt design and validation procedures, to ensure transparency and replicability.

The contribution of this study lies in its dual relevance to methodology and practice. Methodologically, it advances the use of AI as a tool for structuring qualitative decision-support models, addressing gaps in existing literature on AI-assisted policy analysis. Practically, it offers a preliminary framework that may assist policymakers in identifying strategic options and understanding trade-offs within the agribusiness system. The approach has implications for multiple stakeholders, including farmers (through production strategies), supply chain actors (through distribution and market efficiency), local governments (through regional planning), and national institutions (through policy coordination and stabilization mechanisms) (Ansari et al., 2023; Arora et al., 2025; Machefer et al., 2025; Shobur et al., 2025; Zaman et al., 2023).

It is important to note that this study is not an empirical analysis and does not measure the actual condition of food security in Indonesia. The decision tree developed is conceptual and should not be interpreted as a policy-ready tool. Rather, it serves as an exploratory framework that requires further validation through empirical data, expert consultation, and stakeholder engagement before practical application. While AI offers advantages in speed and knowledge integration, its outputs remain subject to limitations such as contextual bias and lack of real-time data.

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Ultimately, this study positions AI not as a replacement for empirical research or expert judgment, but as a complementary tool for enhancing structured thinking and early-stage policy design in complex agribusiness systems. By integrating AI-generated reasoning with established theoretical frameworks, the study contributes to more adaptive and transparent approaches to food security analysis in Indonesia and beyond.

METODE

Research Design

This research adopts a proof-of-concept methodological approach to explore the feasibility of using Chat Generative Pre-trained Transformer (ChatGPT): ChatGPT (GPT-5.3, OpenAI), as the sole input source for constructing a decision tree model aimed at strengthening Indonesia's national food security. ChatGPT accessed via the web interface in April 2026, to generate structured analytical responses based on designed prompts. The design prioritizes methodological innovation and transparency, while maintaining alignment with established theoretical frameworks and validation protocols. Importantly, this study is not intended as an empirical investigation and does not aim to measure or represent the actual condition of food security in Indonesia. Instead, it focuses on demonstrating how AI-generated reasoning can be systematically structured into a conceptual decision-support framework.

The study follows a qualitative–analytical design with an emphasis on methodological exploration rather than empirical generalization. No primary or secondary field data are collected, and all analytical inputs are derived exclusively from AI-generated responses. Consequently, the outputs of this research—particularly the decision tree—should be interpreted as conceptual and exploratory rather than as empirically validated representations of real-world conditions. The primary objective is to assess the plausibility and internal coherence of AI-generated decision pathways, rather than to produce statistically generalizable findings or policy-ready recommendations.

The overall workflow consists of four main stages: (1) research design, (2) AI-based knowledge generation, (3) decision tree construction, and (4) theoretical and literature-based validation. Each stage is carefully documented to ensure methodological transparency, replicability, and critical evaluation. The use of AI in this process is treated as an analytical instrument rather than a source of factual authority, meaning that all outputs are subject to interpretation and validation.

The conceptual framing stage defines the scope and analytical boundaries of the study. Guided by the Food and Agriculture Organization (FAO)'s four-pillar framework—availability, access, utilization, and stability—the research identifies key thematic dimensions of Indonesia's food security system. These dimensions serve as the structural basis for prompt design and subsequent AI interaction. The adoption of the FAO framework ensures theoretical consistency and enables alignment with established food security literature, while also providing a structured lens for organizing AI-generated insights.

AI-Based Data Generation

At the core of the methodology is the use of ChatGPT as a virtual expert system. This stage involves carefully crafted prompt engineering to elicit structured, relevant, and contextually appropriate responses from the AI. Prompt design follows three guiding principles: clarity, specificity, and scope alignment. The prompt used in this study are:

1) Context and Problem Exploration Prompts
   - *"Based on the FAO's four-pillar framework of food security (availability, access, utilization, and stability), provide a detailed assessment of the key challenges facing Indonesia's national food security. For each pillar, identify the top three challenges and explain their causes and potential impacts."*
   - *"Within the context of Indonesia's food security, list and describe the most significant systemic vulnerabilities that could lead to disruptions in each of the FAO's four dimensions: availability, access, utilization, and stability."*

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- *"Identify potential future risks to Indonesia's food security over the next decade, considering environmental, economic, political, and technological factors. Organize your response by the FAO's four pillars."*

2) Decision Tree Development Prompts
   - *"Using the FAO's four pillars of food security, outline a decision tree for strengthening Indonesia's national food security. Start from a high-level strategic decision at the root, branch into multiple strategic options, and for each option, describe possible outcomes or consequences."*
   - *"Generate a qualitative decision tree structure that identifies key decision points for improving food availability, access, utilization, and stability in Indonesia. Include at least two alternative actions for each decision point and explain the trade-offs between them."*
   - *"For the context of Indonesia, create a decision tree focused on improving the stability pillar of food security. Identify major risk factors, possible mitigation strategies, and potential long-term impacts for each strategy."*
   - *"Provide a decision pathway for policymakers in Indonesia to address simultaneous challenges in food availability and access. Structure the response as interconnected decision points, possible actions, and projected outcomes."*
3) Validation and Cross-Checking Prompts
   - *"Compare the AI-generated decision tree for Indonesia's food security with official national policy documents and strategic plans. Identify points of alignment, divergence, and possible reasons for discrepancies."*
   - *"Cross-check the strategies in the AI-generated decision tree against academic literature on food security in Indonesia from the last ten years. Summarize which strategies have strong empirical or theoretical support and which ones are less supported."*
   - *"Evaluate the AI-generated decision tree for potential biases, oversimplifications, or missing perspectives. Suggest improvements based on recognized best practices in food security policy planning."*

Decision Tree Construction

The decision tree is defined as a structured and hierarchical analytical model that organizes decision points (nodes), alternative strategies (branches), and their corresponding outcomes (terminal nodes) into a logical framework. It is used as a conceptual tool to map policy pathways for strengthening Indonesia's food security, based on the four pillars of the Food and Agriculture Organization (FAO): availability, access, utilization, and stability.

This model differs from conventional quantitative decision trees, which rely on probability estimates, statistical calculations, and optimization techniques. Instead, the decision tree developed here is qualitative, constructed from AI-generated reasoning without numerical weighting or probabilistic assumptions. Its purpose is not to predict optimal outcomes, but to provide a structured representation of possible strategic choices and their implications.

The model begins with a root node representing the overarching objective—strengthening national food security—which branches into four primary nodes aligned with the FAO dimensions. These are further expanded into secondary decision nodes reflecting specific policy strategies (e.g., climate-resilient agriculture, distribution improvement, nutrition programs, and price stabilization). Each pathway leads to terminal outcome nodes, describing expected qualitative results such as improved availability, enhanced access, better nutrition, or increased system stability. For clarity, the decision tree is presented in a visual hierarchical diagram showing the directional flow from the root node to decision nodes and terminal outcomes, with labeled branches and arrows to enhance interpretability.

To guide interpretation, each decision node is associated with qualitative criteria, including potential impact, implementation feasibility, resource requirements, institutional capacity, and time horizon. The model also highlights trade-offs between policy options, such as budget constraints between infrastructure investment and subsidies, or tensions between import strategies and domestic production incentives.

Given the absence of empirical probability data, uncertainty is represented through alternative branches rather than probabilistic modeling. Therefore, the decision tree is explicitly qualitative and exploratory, not predictive or prescriptive. It should be interpreted as a conceptual decision-support framework rather than a basis for direct policy implementation.

Validation Protocol

Recognizing that AI-generated outputs may contain biases, oversimplifications, or contextual limitations, this study employs a structured validation protocol to assess the credibility and coherence of the decision tree model. Given the qualitative and conceptual nature of the model, validation is conducted through interpretative cross-referencing rather than statistical testing. The validation process consists of two main components: theoretical validation and policy validation.

1) Theoretical Validation
   Theoretical validation involves comparing each component of the decision tree—root node, decision nodes, branches, and terminal outcomes—against established conceptual frameworks, particularly the FAO's four-pillar model of food security. The objective is to ensure that the structure and logic of the AI-generated decision tree are consistent with recognized theoretical principles. In addition, relevant literature on decision analysis and food security is used to verify whether the identified strategies, decision criteria, and trade-offs are conceptually sound. This step ensures that the model maintains internal coherence and theoretical validity, despite being generated through AI-based reasoning.
2) Policy Validation
   Policy validation is conducted by cross-referencing the AI-generated decision tree with Indonesia's official food security policies, strategic plans, and regulatory frameworks. This includes examining whether the proposed decision nodes and strategic options are aligned with existing national priorities, institutional mandates, and policy instruments. The purpose is not to confirm empirical accuracy, but to assess the contextual relevance and practical plausibility of the model. Through this process, the study identifies areas of convergence between AI-generated recommendations and current policy directions, as well as potential gaps or divergences.

It is important to note that this validation process does not transform the model into an empirical or predictive tool. Instead, it serves as a credibility check to ensure that the qualitative decision tree remains grounded in established theory and policy context. Given the reliance on AI-generated inputs, further validation through empirical data, expert consultation, and stakeholder engagement is necessary before any practical application.

RESULTS AND DISCUSSION

Overview of AI-Generated Decision Tree Outcomes

This study employed Chat Generative Pre-trained Transformer (ChatGPT): ChatGPT (GPT-5.3, OpenAI) as the primary analytical engine to develop a strategic decision tree aimed at strengthening Indonesia's national food security, following the four foundational pillars defined by the Food and Agriculture Organization (FAO): availability, access, utilization, and stability. The decision tree serves as a structured visualization of strategic pathways, branching from overarching goals to actionable policy measures. Unlike conventional decision tree analyses built upon primary or secondary datasets, this model is generated through iterative AI prompting, with cross-validation against theoretical frameworks, official policy documents, and findings from prior studies.

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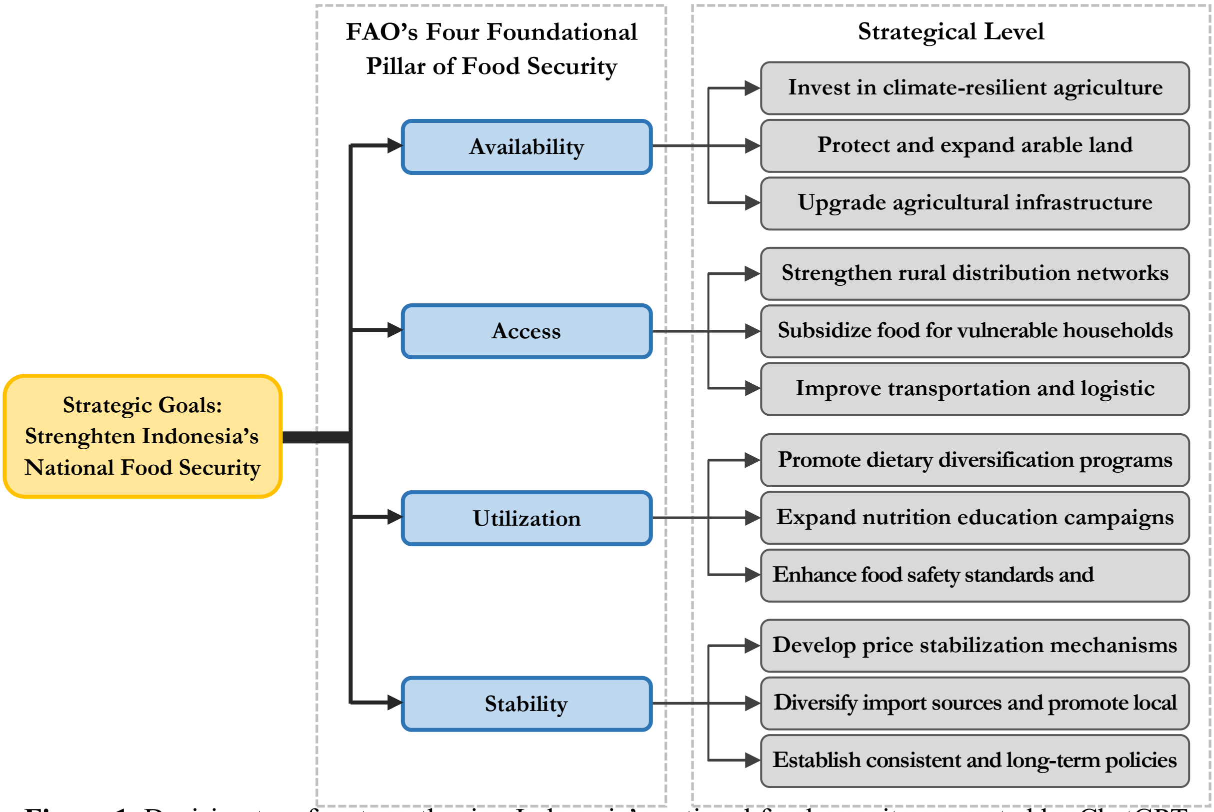

Figure 1. Decision tree for strengthening Indonesia's national food security generated by ChatGPT

From this root, the model branches into the four FAO dimensions. Each dimension further branches into three targeted strategies, creating a multi-level hierarchical structure. The result is a clear mapping from macro-level objectives to micro-level actionable interventions.

Dimension-by-Dimension Analysis

Availability

The dimension of availability refers to the physical presence of adequate quantities of food through domestic production, imports, or national reserves. Without sufficient food in the system, no amount of improvement in access, utilization, or stability can resolve the fundamental challenge of feeding the population. In Indonesia, availability has historically been influenced by agricultural productivity, land use patterns, and the robustness of infrastructure supporting production and distribution. The AI-generated decision tree proposes three interlinked strategies to enhance availability:

1) Invest in climate-resilient agriculture

   This approach recognizes Indonesia's vulnerability to climatic events such as El Niño and La Niña, which can disrupt planting and harvesting cycles, reduce yields, and increase the volatility of food supply. Climate-resilient agriculture may involve breeding drought-tolerant and flood-resistant crop varieties, introducing adaptive planting calendars, and implementing precision agriculture technologies. These innovations are in line with FAO's recommendations for climate adaptation in agriculture and mirror policy initiatives already being explored by the Indonesian Ministry of Agriculture (Algieri et al., 2025; Erdogan et al., 2024; Meng & Qian, 2024; Suryana, 2014; Wright & Meylinah, 2017).

2) Protect and expand arable land

Urbanization and industrial expansion have led to a gradual reduction in agricultural land, particularly in Java, where much of Indonesia's rice production is concentrated. AI's inclusion of this strategy reflects awareness of land-use competition, but the decision tree itself does not quantify the extent of land needed to meet future food demands. Still, the emphasis on legal protections, zoning regulations, and incentives for sustainable land management is consistent with government programs aimed at curbing land conversion (Cattaneo et al., 2021; Ma'Mun et al., 2021; Ty et al., 2021).

3) Upgrade agricultural infrastructure

The third availability strategy is upgrading agricultural infrastructure, including irrigation systems, storage facilities, and mechanization. Efficient irrigation not only increases yields but also allows for multiple cropping cycles in a year. Storage facilities reduce post-harvest losses, while mechanization can address labor shortages in rural areas. These priorities are supported by empirical findings in the Indonesian context, where inefficient irrigation and inadequate storage account for significant production losses. However, while AI correctly identifies infrastructure as a core driver of availability, it does not automatically integrate the fiscal and logistical constraints that may limit rapid scaling (Nuryanti et al., 2017; Okura et al., 2022).

Access

The dimension of access focuses on the ability of individuals and households to physically and economically obtain the food they need. Even if sufficient quantities of food are available in aggregate, disparities in income, infrastructure, and market integration can prevent equitable access. In Indonesia, access is shaped by a combination of purchasing power, geographic isolation, and the efficiency of distribution networks. The AI-generated decision tree suggests three strategies to enhance food access:

1) Strengthen rural distribution networks

The decision tree identifies strengthening rural distribution networks as a foundational intervention. Many rural and remote areas in Indonesia, particularly in eastern provinces such as Papua and Maluku, face chronic challenges in moving goods from production centers to consumers. Weak distribution networks lead to high transportation costs, increased food prices, and seasonal shortages. AI's recommendation to enhance rural logistics aligns with studies linking improved distribution systems to reduced post-harvest losses and better price stability. Investments in rural roads, storage hubs, and market linkages could significantly enhance accessibility ([FAO] Food and Agriculture Organization, 2020; Achmad et al., 2021; Ji et al., 2024).

2) Subsidize food for vulnerable households

A second access strategy is subsidizing food for vulnerable households, ensuring that low-income families can afford basic staples. Indonesia's existing Bantuan Pangan Non-Tunai (BPNT) program serves as a national model for this approach, providing electronic vouchers that can be redeemed for staple foods. While AI readily identifies subsidies as a tool for improving access, it does not evaluate the fiscal sustainability of such programs, an important consideration for long-term implementation. Nevertheless, subsidies remain a vital short-term measure in mitigating food insecurity among the most vulnerable groups (Bernaschi et al., 2023; Brennan, 2003; Gopinath et al., 2004; Pandey & Mishra, 2024; Rashid et al., 2005).

3) Improve transportation and logistics systems

The third access strategy is improving transportation and logistics systems at a broader, national scale. While strengthening rural networks addresses local bottlenecks, integrated national transportation systems ensure that surplus food from one region can quickly reach deficit regions. For an archipelagic nation like Indonesia, this includes not only roads but also ports, ferries, and cold chain systems. AI's inclusion of this point reflects an understanding of the unique logistical challenges posed by Indonesia's geography. Evidence from past policy interventions shows that integrated transport systems can reduce price disparities between urban and rural markets, improving both physical and economic access to food (Chauhan et al., 2021; Lavelli, 2021; Perdana et al., 2020).

In sum, AI's access-related strategies are grounded in well-established principles of food distribution and market integration. Their strength lies in the recognition of both local and national logistics as separate but complementary challenges. However, without integration of cost-effectiveness analysis or stakeholder capacity assessment, these strategies remain at a conceptual rather than operational level.

Utilization

The dimension of utilization concerns how food is used and metabolized, emphasizing nutritional adequacy, food safety, and dietary diversity. This pillar acknowledges that having sufficient and affordable food is insufficient if the food consumed does not meet nutritional needs or is unsafe. In Indonesia, utilization challenges manifest in persistent stunting rates among children, micronutrient deficiencies, and foodborne illnesses. Utilization addresses nutritional value, food safety, and dietary diversity. The AI-generated decision tree suggests three strategies to enhance food utilizaation:

1) Promote dietary diversification programs

   This strategy aims to reduce Indonesia's dependence on rice as the primary staple and encourage consumption of nutrient-rich alternatives such as maize, cassava, sago, and various legumes. Diversification also extends to increasing consumption of vegetables, fruits, and animal proteins. This approach aligns with FAO's recommendations for balanced diets and has the added benefit of reducing vulnerability to price shocks in any single commodity. While AI correctly identifies diversification as a key intervention, it does not propose culturally tailored approaches to encourage behavioral change, which could improve adoption rates (Mohamed et al., 2025; Nurhasan et al., 2024; Suryana, 2014; Yamaguchi et al., 2022).

2) Expand nutrition education campaigns

   The second utilization strategy involves expanding nutrition education campaigns. Education initiatives can improve knowledge of balanced diets, safe food handling practices, and infant feeding techniques. School-based programs, public service announcements, and community workshops are potential vehicles for such campaigns. Literature from similar interventions in Southeast Asia shows that improved nutrition literacy can lead to significant reductions in malnutrition indicators. However, AI does not automatically specify the most effective channels for education delivery in rural versus urban settings, suggesting a need for context-specific program design (Haq et al., 2022; Mohamed et al., 2025; Sisay, 2024; Suryana, 2014).

3) Enhance food safety standards and practices

   The third strategy is enhancing food safety standards and practices. Food safety is essential not only for public health but also for maintaining consumer confidence and meeting export requirements. AI's inclusion of this measure reflects global priorities in reducing foodborne illness and contamination. In the Indonesian context, this could involve stricter enforcement of hygiene regulations in food markets, improved inspection systems, and expanded laboratory capacity for detecting contaminants. While AI captures the essence of food safety as part of utilization, it does not inherently assess institutional capacity for enforcement, which could be a critical limiting factor (Suárez et al., 2024; Walls et al., 2019; Wang et al., 2025).

FAO's State of Food Security and Nutrition in the World reports indicate that countries with proactive nutrition education exhibit reduced stunting rates, affirming this branch's policy relevance. Overall, AI's utilization strategies align with both global frameworks and Indonesia's national priorities, particularly in tackling malnutrition and improving public health outcomes. The challenge lies in translating these broad strategies into culturally and institutionally feasible programs.

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Stability

The stability dimension ensures that the other three pillars—availability, access, and utilization—are maintained over time, even in the face of economic, environmental, or political shocks. Stability is particularly relevant for Indonesia due to its exposure to climate variability, global market volatility, and domestic political cycles.

1) Develop price stabilization mechanisms
   The first stability strategy identified by AI is developing price stabilization mechanisms. This could involve maintaining buffer stocks, implementing variable import tariffs, or using targeted subsidies during periods of price spikes. Such measures aim to protect consumers from sudden increases in food costs and to safeguard farmers from drastic drops in commodity prices. Historical evidence from Indonesia's Badan Urusan Logistik (BULOG) shows that well-managed stockpiles can contribute to price stability, though they also entail significant fiscal and logistical challenges (Sapthu et al., 2024; Shobur et al., 2025).
2) Diversify import sources and promote local production
   The second strategy focuses on diversifying import sources and promoting local production. This dual approach reduces dependency on a single supplier or trade route, thereby minimizing vulnerability to geopolitical tensions or supply chain disruptions. AI's recognition of this strategy reflects an understanding of global interdependence in food trade. In practice, diversification could mean establishing new trade agreements while simultaneously supporting domestic producers through subsidies or technical assistance (Ansari et al., 2023; Malau et al., 2023).
3) Establish consistent and long-term food policies
   The third stability strategy is establishing consistent and long-term food policies. Political shifts often lead to changes in policy priorities, which can undermine the stability of food systems. AI emphasizes the importance of maintaining continuity in strategic objectives, regardless of changes in administration. This could involve embedding food security goals in long-term national development plans, supported by bipartisan legislative commitments. While AI accurately identifies this need, it does not address the political economy dynamics that might impede policy continuity, such as competing interests among stakeholders (Arora et al., 2025; Chaudhry et al., 2021; Putra et al., 2021).

Collectively, the stability strategies proposed by AI are theoretically sound and consistent with both FAO guidance and Indonesian policy discourse. The main limitation is the absence of detailed mechanisms for implementation and monitoring, which would be essential for sustaining long-term food security. While these strategies are theoretically sound, real-world implementation faces political economy constraints, an aspect that AI outputs may underrepresent unless explicitly prompted.

Validation Protocol

The validation of an AI-generated decision tree for strengthening Indonesia's national food security requires a systematic comparative assessment to ensure that the proposed strategies are both conceptually sound and aligned with existing national frameworks. This assessment is divided into two complementary components.

Theoretical Validation

The analysis reveals a strong correspondence between the AI's structure and the FAO framework. The AI's categorization of climate-resilient agriculture, land preservation, and agricultural infrastructure upgrades under the availability dimension is directly consistent with FAO's definition, which emphasizes the importance of physical food supply through production, imports, and reserves. Similarly, access-related strategies such as rural distribution strengthening, targeted subsidies, and integrated logistics systems closely reflect theoretical principles of equitable distribution and economic affordability.

The utilization dimension also demonstrates theoretical congruence, with dietary diversification, nutrition education, and food safety measures aligning with literature on nutrition-sensitive food systems. Furthermore, the stability strategies—including price stabilization, diversification of import sources, and long-term policy continuity—are firmly embedded in the stability definition, which emphasizes resilience to shocks.

However, the theoretical validation process also identifies certain omissions. While the AI framework includes adaptation to climate variability under availability and stability, it does not explicitly integrate the concept of adaptive governance—a theoretical construct emphasizing iterative learning and participatory decision-making in food security governance. Similarly, the AI's structure lacks explicit mention of gender equity and social inclusion, which are increasingly recognized in contemporary theoretical models as cross-cutting enablers of all four food security dimensions.

Policy Validation

Policy validation involves benchmarking the AI-generated decision tree against the Indonesian government's formal strategies, laws, and action plans related to food security. This ensures that AI recommendations are not only theoretically sound but also practically relevant and politically actionable within the national context. The most relevant reference documents for this validation include:

1) Law No. 18/2012 on Food, which provides the legal basis for national food policy.
2) National Food Security Policy and Action Plan (RAN-PG), outlining strategic objectives for the medium and long term.
3) Ministry of Agriculture Strategic Plan, which details sectoral programs for agricultural development.
4) National Medium-Term Development Plan (RPJMN), which integrates food security as part of broader socio-economic development goals.

A side-by-side comparison indicates a high degree of alignment between AI-generated recommendations and these policy instruments. For instance, the AI's emphasis on climate-resilient agriculture and irrigation upgrades matches RAN-PG's strategic objectives for sustainable agricultural intensification. Similarly, the AI's focus on improving distribution networks parallels RPJMN targets for rural infrastructure development.

In utilization, the AI's proposals for nutrition education and food safety correspond directly to the Ministry of Health's programs under the Gerakan Masyarakat Hidup Sehat (GERMAS) initiative. Stability measures such as buffer stock management and diversified sourcing align with BULOG's operational mandates and trade diversification strategies outlined in the Ministry of Trade's plans.

Nonetheless, policy validation also identifies certain divergences. The AI framework suggests broadening subsidies to ensure universal access for vulnerable households, but current national policy trends are moving toward targeted assistance to optimize budget efficiency. Similarly, while AI proposes the establishment of long-term bipartisan food security policies, the actual political and legislative mechanisms to achieve such continuity are not explicitly present in current frameworks—reflecting a gap between AI's idealized recommendation and the political realities of Indonesia's governance system.

An additional observation from the policy validation process is that AI recommendations generally lack explicit references to implementation sequencing—the staged, time-bound roll-out of policy measures to ensure feasibility. National policies often prioritize certain interventions based on available resources and institutional capacity, whereas the AI model presents them in parallel, potentially underestimating the practical constraints of simultaneous execution.

Discussion on Convergence and Divergence

The comparative assessment of the AI-generated decision tree through both theoretical and policy validation reveals a generally high degree of alignment, with notable areas of convergence and certain strategic divergences that warrant closer scrutiny. This dual lens approach allows for a richer understanding of how AI-driven frameworks may complement, reinforce, or challenge existing conceptual and policy paradigms in the context of Indonesia's food security.

From the perspective of convergence, the AI-generated model exhibits strong fidelity to the FAO's four-pillar theoretical structure. Each major branch—availability, access, utilization, and stability—is populated with interventions that are not only conceptually consistent but also practically relevant within Indonesia's socio-economic and environmental landscape. The model's prioritization of climate-resilient agriculture, enhanced distribution networks, dietary diversification, and price stabilization reflects a coherent integration of theory and praxis. The parallel with national policies is equally pronounced: most AI recommendations find direct counterparts in Indonesia's Rencana Aksi Nasional Pangan dan Gizi (RAN-PG), the Rencana Pembangunan Jangka Menengah Nasional (RPJMN), and sectoral plans from the Ministry of Agriculture, Ministry of Trade, and Ministry of Health.

This degree of alignment underscores the credibility and practical utility of AI-assisted decision modeling when coupled with well-defined theoretical frameworks and a structured prompting methodology. It also suggests that large language models like ChatGPT can serve as effective rapid prototyping tools for policy scenario design, especially when time and resources for traditional multi-stakeholder consultations are limited.

However, the divergences identified during the validation process are equally instructive. On the theoretical front, the AI model omits certain cross-cutting dimensions—such as gender equity, social inclusion, and adaptive governance—that have gained prominence in recent academic discourse. These omissions are not merely academic gaps; they represent potential blind spots in real-world implementation, where issues of inclusivity and adaptive capacity often determine the long-term sustainability of food security interventions.

On the policy side, divergences emerge primarily in two domains: scope of subsidies and sequencing of interventions. AI's recommendation to expand subsidies universally to all vulnerable groups contrasts with the current government's fiscal strategy of targeted assistance. While AI's approach maximizes theoretical inclusivity, it may be financially unsustainable or politically contentious within existing budgetary constraints. Similarly, AI presents many interventions as simultaneously actionable, whereas actual policy documents prioritize staged implementation to account for institutional capacity, budget cycles, and political feasibility.

Interestingly, some divergences reflect idealistic optimism inherent in AI reasoning, where the absence of political economy constraints allows for recommendations that, while desirable in principle, may be challenging in practice. This gap between the AI's "clean" logic and the messiness of policy reality highlights the importance of human-AI complementarity—where human expertise and contextual judgment temper the AI's output to produce more implementable strategies.

In summary, the convergence points reinforce the reliability of the AI-generated decision tree as a conceptually grounded and policy-relevant framework, while the divergences provide valuable signals for refinement. Addressing these gaps through iterative prompt adjustments, targeted inclusion of cross-cutting themes, and explicit integration of political economy considerations could significantly enhance the model's readiness for adoption in real-world policy contexts.

Policy Implications

Prioritization and Sequencing of Interventions

One of the most immediate policy implications lies in the need for strategic prioritization of interventions within each FAO dimension. The AI-generated decision tree presents a wide array of recommendations across availability, access, utilization, and stability; however, the feasibility of simultaneous execution is constrained by budgetary, institutional, and logistical factors. Translating the decision tree into policy action requires sequencing measures based on impact potential, cost-effectiveness, and alignment with ongoing national programs.

For instance, in the availability dimension, interventions such as upgrading irrigation systems and promoting climate-resilient crops should be prioritized in regions with high vulnerability to drought, while longer-term measures such as soil regeneration programs can be implemented in parallel with ongoing agricultural extension services. In access, improvements in distribution infrastructure can be synchronized with targeted social protection schemes, thereby ensuring that physical availability is matched by economic accessibility.

Institutional Implications: Enhancing Cross-Sector Coordination

The decision tree emphasizes multi-faceted interventions that cut across ministerial mandates, necessitating enhanced cross-sector coordination. Stability-related measures such as buffer stock management involve the National Logistics Agency (BULOG), the Ministry of Trade, and the Ministry of Agriculture, while utilization-focused interventions like nutrition education require close collaboration between the Ministry of Health and the Ministry of Education. Without robust inter-agency mechanisms, even well-designed strategies risk fragmentation.

A policy implication emerging from this observation is the potential role of an integrated Food Security Coordination Unit—possibly embedded within the National Development Planning Agency (Bappenas)—to oversee the alignment, monitoring, and evaluation of multi-sector food security strategies. This aligns with global best practices, where cross-sector governance bodies ensure that policies are not only coherent but also adaptive to emerging challenges.

Bridging the Gap between Idealism and Policy Reality

The divergences identified in policy validation—particularly around universal subsidies and simultaneous implementation—underscore the tension between idealized recommendations and practical constraints. Policymakers can bridge this gap by using the decision tree as an aspirational blueprint, while selectively adapting recommendations to fiscal realities, political feasibility, and institutional capacity.

This adaptation process can be supported by policy simulation exercises, where different configurations of the decision tree are tested under varying budgetary and political scenarios. Such exercises can help identify “quick wins” that deliver high impact with minimal resource demands, while also mapping out longer-term interventions for gradual implementation.

International and Regional Policy Relevance

Finally, while the decision tree is tailored to Indonesia’s context, its structure and methodology have potential relevance for other countries in Southeast Asia facing similar food security challenges. Indonesia could play a leading role in sharing AI-assisted policy modeling approaches through ASEAN platforms or South-South cooperation initiatives, positioning itself as a regional innovator in the integration of AI into public policy.

In summary, the policy implications of this study extend beyond the specific recommendations of the decision tree. They highlight the need for strategic sequencing, cross-sector coordination, theoretical inclusivity, and methodological innovation in policy formulation. By treating the AI-generated model not as a fixed blueprint but as a dynamic decision-support tool, policymakers can harness its strengths while mitigating its limitations, ultimately contributing to a more resilient, inclusive, and adaptive national food security strategy.

Implications for Policy Monitoring and Evaluation (M&E)

The decision tree’s structured, hierarchical format lends itself naturally to policy monitoring and evaluation frameworks. Each node and sub-node can be linked to measurable indicators, enabling policymakers to track progress and adjust strategies in real time. Embedding these indicators within Indonesia’s existing M&E systems—such as those operated by Bappenas and Statistics Indonesia (BPS)—would enhance accountability and ensure that strategies remain adaptive to emerging trends.

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Methodological Implications and Discussions

AI as a Policy Prototyping Tool

Perhaps the most novel policy implication is methodological: the demonstrated utility of AI, specifically ChatGPT, as a policy prototyping tool. The structured decision tree produced in this study illustrates how AI can rapidly synthesize theoretical frameworks, empirical insights, and strategic recommendations into a coherent model. While AI outputs require careful validation and adaptation to local contexts, they can significantly reduce the time needed to formulate preliminary policy options.

This has particular relevance for time-sensitive policy environments, such as during climate-related shocks or commodity price volatility, where rapid scenario development is crucial. Embedding AI-assisted prototyping into the policy cycle—particularly at the problem-identification and option-generation stages—could strengthen Indonesia's capacity for evidence-informed decision-making.

Addressing Theoretical Gaps through Policy Integration

The theoretical validation revealed omissions related to gender equity, social inclusion, and adaptive governance. These gaps present an opportunity for policymakers to integrate cross-cutting principles into national food security strategies more explicitly. Targeted agricultural training for women farmers, inclusive market access programs for marginalized groups, and governance structures that institutionalize feedback loops from local stakeholders could be embedded into the decision tree's recommended actions.

Incorporating these dimensions would not only bring the strategy in line with contemporary food security theory but also enhance its resilience by ensuring that interventions address structural inequities and promote inclusive participation.

Comparative Assessment Against AI-Generated Decision Tree

These findings suggest that while AI-generated recommendations are conceptually well-aligned with the grand theoretical framework, additional theoretical depth could be achieved by integrating these overlooked dimensions. This underscores the need for prompt engineering that explicitly instructs AI to incorporate cross-cutting principles into its decision-making logic.

The AI-generated model mirrors the FAO four-pillar framework almost perfectly, indicating strong alignment with established theory. Compared to Indonesia's Rencana Pembangunan Jangka Menengah Nasional (RPJMN), the decision tree covers similar priorities but offers a cleaner hierarchical visualization. Notably, AI's approach tends to:

1) Avoid overly technical sub-branches unless specifically asked.
2) Provide balanced coverage across all four pillars, preventing overemphasis on availability alone (a common bias in policy documents).
3) Lack direct integration of cost–benefit estimates, which remains a limitation for decision-makers.

Strengths of the AI-Assisted Approach

The integration of AI into decision tree modeling for food security analysis offers several strengths that enhance both the efficiency and comprehensiveness of policy development.

Rapid model generation

Speed and scalability stand out as significant advantages. The decision tree was produced within minutes, compared to potentially weeks of human-only workshops. Generating a conceptually coherent and theoretically informed decision tree using traditional expert consultations can be a time-intensive process, often requiring months of stakeholder engagement. AI, by contrast, can produce a baseline model within hours, enabling rapid prototyping in situations where timely policy responses are critical—such as during natural disasters, global supply chain disruptions, or price shocks.

Broad thematic coverage

AI efficiently integrates multidisciplinary considerations (agriculture, economics, public health, trade). the AI-assisted approach benefits from extensive knowledge integration. Trained on vast amounts of textual data, large language models such as ChatGPT can synthesize diverse sources—including academic research, policy documents, and historical precedents—into a unified analytical framework. This breadth enables the decision tree to incorporate both high-level strategic concepts and granular operational measures.

Consistency in logical structure is also a notable strength. The AI-generated decision tree adheres to a hierarchical logic that ensures all recommendations are clearly nested under broader strategic objectives. This structural clarity facilitates downstream tasks such as indicator development, monitoring, and evaluation

Adaptability

This approach offers flexibility for iterative refinement. Prompts can be iteratively refined to add detail, adjust policy focus, or incorporate stakeholder perspectives. By documenting the prompts used and systematically adjusting them, researchers and policymakers can generate alternative scenarios, stress-test assumptions, and adapt recommendations to evolving circumstances. This iterative capability is particularly valuable in dynamic policy environments.

Replicability

Documented prompts (see Methodology section) allow other researchers to replicate and modify the model. The AI-assisted method has educational and capacity-building potential. In contexts where policy teams may have limited experience in structured decision modeling, AI outputs can serve as templates or learning tools, helping to build local analytical capacity while delivering immediate practical outputs.

Limitations

Despite its advantages, the AI-assisted approach is not without limitations, many of which stem from the nature of large language models and the conditions under which they operate.

Dependence on training data

AI's outputs limitation is data provenance and temporal relevance. AI's outputs are shaped by its pretraining corpus, potentially omitting highly localized challenges. AI models like ChatGPT are trained on large datasets, but the specific sources, dates, and regional applicability of the information are often opaque. This means that some recommendations may be based on outdated, globally generalized, or non-Indonesian contexts, requiring careful human vetting to ensure local relevance.

If the bulk of its food security knowledge comes from sources rooted in specific geopolitical or cultural perspectives, the resulting decision tree might underrepresent alternative approaches more suited to Indonesia's unique socio-economic realities. This can manifest in overemphasis on certain technological solutions while underplaying local, community-driven strategies.

Lack of quantitative grounding

AI suggestions are qualitative and may require statistical modeling for prioritization. Without continuous retraining or connection to live data sources, the AI cannot incorporate the latest developments in Indonesian agricultural policy, market dynamics, or climatic conditions. This limits its utility for real-time decision-making unless supplemented by updated datasets or expert inputs.

Risk of confirmation bias

The process of prompt engineering itself introduces bias. If prompts are too narrowly framed, AI may reinforce existing assumptions instead of challenging them. The structure, wording, and scope of the prompts used to query the AI significantly shape its outputs. Inadequate or overly narrow prompts may omit relevant dimensions, while excessively broad prompts may produce unfocused or impractical recommendations. This underscores the necessity of transparency in prompt documentation and iterative refinement.

Absence of political feasibility analysis

AI-generated models are policy-neutral and do not inherently weigh political constraints. Because AI operates in a context-free environment, it may recommend strategies that are theoretically sound but practically infeasible due to fiscal constraints, political resistance, or institutional capacity gaps. This idealism can lead to overly ambitious recommendations that require substantial adaptation before implementation.

Furthermore, It is crucial to emphasize that the decision tree produced in this study is inherently conceptual in nature. It represents a structured synthesis of AI-generated reasoning rather than a model derived from empirical data or statistical estimation. As such, the decision tree should not be interpreted as a definitive guide for policy implementation, but rather as an exploratory framework intended to support discussion, hypothesis development, and further empirical investigation. The model illustrates possible strategic pathways and relationships between policy options, but does not quantify impacts, probabilities, or trade-offs in a manner required for direct policy execution.

The findings of this study are not designed to serve as an immediate basis for policymaking. While the AI-generated model provides a structured representation of potential strategies, its application in real-world contexts requires careful adaptation, contextualization, and validation. Policymakers should therefore treat the results as a preliminary analytical reference that must be complemented by empirical data, stakeholder consultation, and institutional assessment before being translated into actionable policies.

Finally, the use of Artificial Intelligence in this research necessitates a critical validation process. AI-generated outputs, including those produced by ChatGPT, may be influenced by limitations such as lack of contextual specificity, potential bias embedded in training data, and absence of real-time information. To address these challenges, this study incorporates a validation stage that compares AI outputs with established theories, official policy documents, and relevant academic literature. Nevertheless, this validation is interpretative rather than empirical, and further validation through data-driven analysis and expert review remains essential for any practical application.

CONCLUSION

This study presents a methodological proof-of-concept demonstrating the feasibility of using ChatGPT to construct a qualitative decision tree for food security analysis in Indonesia. The resulting model, structured around the FAO's four-pillar framework, offers a conceptually plausible and potentially policy-relevant mapping of strategic pathways rather than an empirically validated or predictive tool. It illustrates how AI-generated reasoning can be organized into a transparent, hierarchical framework that links overarching objectives to possible policy actions across availability, access, utilization, and stability dimensions.

However, the findings remain exploratory and non-empirical. The decision tree does not measure actual food security conditions, incorporate probabilistic estimates, or evaluate policy effectiveness. As such, it should not be interpreted as a final basis for policymaking. Instead, it serves as an initial analytical reference that highlights possible strategies and trade-offs, which require further validation through empirical data, expert judgment, and institutional processes. Limitations related to contextual specificity, lack of quantitative grounding, and potential bias in AI-generated outputs reinforce the need for cautious interpretation.

Overall, this study underscores that AI can function as a supporting tool for policy prototyping, offering speed and integrative capacity, but its outputs must be rigorously validated and refined before practical application in food security governance.

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REFERENCES

[FAO] Food and Agriculture Organization. (2020). *Addressing the Impacts of COVID-19 in Food crises April–December 2020: FAO's Component of the Global COVID-19 Humanitarian Response Plan* (Vol. 2019, Issue December). https://doi.org/https://doi.org/10.4060/ca8497en

[FAO] Food and Agriculuture Organization. (2021). *The State of Food Security and Nutrition in The World 2021*. Food and Agriculuture Organization. https://fscluster.org/news/state-food-security-and-nutrition-world-2#:~:text=Around a tenth of the,the previous five years combined.

Achmad, A. L. H., Chaerani, D., & Perdana, T. (2021). Designing a food supply chain strategy during COVID-19 pandemic using an integrated Agent-Based Modelling and Robust Optimization. *Heliyon*, *7*(1207), e08448. https://doi.org/10.1016/j.heliyon.2021.e08448

Adamchick, J., & Perez, A. M. (2020). Choosing Awareness Over Fear: Risk Analysis and Free Trade Support Global Food Security. *Global Food Security*, *26*(September), 100445. https://doi.org/10.1016/j.gfs.2020.100445

Algieri, B., Kornher, L., & von Braun, J. (2025). The changing drivers of inflation – the case of food: Macroeconomics, speculation, climate change and war. *Structural Change and Economic Dynamics*, *75*, 782–800. https://doi.org/https://doi.org/10.1016/j.strueco.2025.10.006

Allahyari, M. S., Berjan, S., El Bilali, H., Ben Hassen, T., & Marzban, S. (2025). Assessing the use of ChatGPT among agri-food researchers: A global perspective. *Journal of Agriculture and Food Research*, *19*, 101616. https://doi.org/https://doi.org/10.1016/j.jafr.2024.101616

Ansari, A., Pranesti, A., Telaumbanua, M., Alam, T., Taryono, Wulandari, R. A., Nugroho, B. D. A., & Supriyanta. (2023). Evaluating the effect of climate change on rice production in Indonesia using multimodelling approach. *Heliyon*, *9*(9), e19639. https://doi.org/https://doi.org/10.1016/j.heliyon.2023.e19639

Arora, N., Bhagat, S., Dhama, R., & Bagler, G. (2025). Machine learning and natural language processing models to predict the extent of food processing. *Journal of Food Composition and Analysis*, *146*, 107938. https://doi.org/https://doi.org/10.1016/j.jfca.2025.107938

Bernaschi, D., Marino, D., Cimini, A., & Mazzocchi, G. (2023). The Social Exclusion Perspective of Food Insecurity : The Case of Blacked-Out Food Areas. *Sustainability*, *15*(2974), 1–18. https://doi.org/https://doi.org/10.3390/su15042974

Brennan, D. C. (2003). Price dynamics in the Bangladesh rice market: implications for public intervention. *Agricultural Economics*, *29*(1), 15–25. https://ageconsearch.umn.edu/record/177986?ln=en

Cao, G., Kornher, L., & Brandi, C. (2025). How robust are machine learning approaches for improving food security amid crises? - Evidence from COVID-19 in Uganda. *World Development*, *196*, 107171. dhttps://doi.org/https://doi.org/10.1016/j.worlddev.2025.107171

Cattaneo, A., Federighi, G., & Vaz, S. (2021). The environmental impact of reducing food loss and waste: A critical assessment. *Food Policy*, *98*, 101890. https://doi.org/https://doi.org/10.1016/j.foodpol.2020.101890

Chaudhry, I., Suleman, R., Bhatti, A., & Ullah, I. (2021). Review: Food price Fluctuations and Its

Influence on Global Food Market. *Annals of Social Sciences and Perspective*, *2*(1), 21–33. https://doi.org/10.52700/assap.v2i1.33

Chauhan, C., Dhir, A., Ul, M., & Salo, J. (2021). Food loss and waste in food supply chains . A systematic literature review and framework development approach. *Journal of Cleaner Production*, *295*, 126438. https://doi.org/10.1016/j.jclepro.2021.126438

Erdogan, S., Kartal, M. T., & Pata, U. K. (2024). Does Climate Change Cause an Upsurge in Food Prices? *Foods*, *13*(1), 1–20. https://doi.org/10.3390/foods13010154

Gopinath, M., Mullen, K., & Gulati, A. (2004). *Domestic support to agriculture in the European Union and the united states: Policy developments since 1996* (Working or Discussion Paper). https://ageconsearch.umn.edu/record/60452?ln=en

Haq, S. U., Shahbaz, P., Abbas, A., Batool, Z., Alotaibi, B. A., & Tratore, A. (2022). Tackling Food and Nutrition Insecurity among Rural Inhabitants : Role of Household-Level Strategies with a Focus on Value Addition , Diversification and Female Participation. *Land*, *11*(254), 1–19. https://doi.org/https://doi.org/10.3390/land11020254

Ji, G., Zhong, H., Feukam Nzudie, H. L., Wang, P., & Tian, P. (2024). The Structure, Dynamics, and Vulnerability of the Global Food Trade Network. *Journal of Cleaner Production*, *434*, 140439. https://doi.org/https://doi.org/10.1016/j.jclepro.2023.140439

Lavelli, V. (2021). Circular food supply chains – Impact on value addition and safety. *Trends in Food Science & Technology*, *114*, 323–332. https://doi.org/https://doi.org/10.1016/j.tifs.2021.06.008

Ma'Mun, S. R., Loch, A., & Young, M. D. (2021). Sustainable irrigation in Indonesia: A case study of Southeast Sulawesi Province. *Land Use Policy*, *111*, 105707. https://doi.org/https://doi.org/10.1016/j.landusepol.2021.105707

Machefer, M., Thomas, A.-C., Meroni, M., Veiga Lopez Pena, J. M., Ronco, M., Corbane, C., & Rembold, F. (2025). Potential and limitations of machine learning modeling for forecasting Acute Food Insecurity. *Global Food Security*, *45*, 100859. https://doi.org/https://doi.org/10.1016/j.gfs.2025.100859

Malau, L. R. E., Rambe, K. R., Ulya, N. A., & Purba, A. G. (2023). The Impact Of Climate Change On Food Crop Production In Indonesia: *Jurnal Penelitian Pertanian Terapan*, *23*(1), 34–46. https://doi.org/10.25181/jppt.v23i1.2418

Meng, H., & Qian, L. (2024). Performances of Different Yield-Detrending Methods in Assessing the Impacts of Agricultural Drought and Flooding: A Case Study in The Middle-and-Lower Reach of the Yangtze River, China. *Agricultural Water Management*, *296*(July 2023), 108812. https://doi.org/10.1016/j.agwat.2024.108812

Mohamed, J. H., Aweke, C. S., & Muleta, T. T. (2025). Impact of Livelihood Diversification on Rural Households ' Food and Nutrition Security : Evidence from West Shoa Zone of Oromia Regional. *Food and Nutrition Policy*, *9*(December 2024). https://doi.org/10.1016/j.cdnut.2024.104521

Nurhasan, M., Ariesta, D. L., Utami, M. M. H., Fahim, M., Aprillyana, N., Maulana, A. M., & Ickowitz, A. (2024). Dietary transitions in Indonesia: the case of urban, rural, and forested areas. *Food Security*, *16*(6), 1313–1331. https://doi.org/10.1007/s12571-024-01488-3

Nuryanti, S., Hakim, D. B., Siregar, H., & Sawit, M. H. (2017). Political economic analysis of rice self-sufficiency in Indonesia. *Indonesian Journal of Agricultural Science*, *18*(2), 77–86. https://doi.org/http//dx.doi.org/10.21082/ijas.v.18.n2.2017.p.77–86

Okura, F., Budiasa, I. W., & Kato, T. (2022). Exploring a Balinese irrigation water management system using agent-based modeling and game theory. *Agricultural Water Management*, *274*, 107951. https://doi.org/https://doi.org/10.1016/j.agwat.2022.107951

Pandey, D. K., & Mishra, R. (2024). Towards sustainable agriculture: Harnessing AI for global food security. *Artificial Intelligence in Agriculture*, *12*, 72–84. https://doi.org/https://doi.org/10.1016/j.aiia.2024.04.003

Perdana, T., Chaerani, D., Achmad, A. L. H., & Hermiatin, F. R. (2020). Scenarios for handling the impact of COVID-19 based on food supply network through regional food hubs under uncertainty. *Heliyon*, *6*(10), 1–22. https://doi.org/10.1016/j.heliyon.2020.e05128

Putra, A. W., Supriatna, J., Koestoer, R. H., & Soesilo, T. E. (2021). Differences in Local Rice Price Volatility, Climate, and Macroeconomic Determinants in the Indonesian Market. *Sustainability*, *13*(8). https://doi.org/10.3390/su13084465

Rashid, S., Jr., R. C., & Gulati, A. (2005). *Grain marketing parastatals in Asia: why do they have to change now?* (p. 75). International Food Policy Research Institute. https://ageconsearch.umn.edu/record/59830?ln=en

Sapthu, A., Louhenapessy, F. H., Saptenno, F., Louhenapessy, D., Duwila, U., & Jani. (2024). Analysis of the Elasticity of Rice Demand for Poor Households in Sirimau District, Ambon City in 2024. *ARRUS Journal of Social Sciences and Humanities*, *4*(3), 419–428. https://doi.org/10.35877/soshum2684

Shobur, M., Nyoman Marayasa, I., Bastuti, S., Muslim, A. C., Pratama, G. A., & Alfatiyah, R. (2025). Enhancing food security through import volume optimization and supply chain communication models: A case study of East Java's rice sector. *Journal of Open Innovation: Technology, Market, and Complexity*, *11*(1), 100462. https://doi.org/https://doi.org/10.1016/j.joitmc.2024.100462

Sisay, K. (2024). Impacts of multiple livelihood diversification strategies on diet quality and welfare of smallholder farmers: Insight from Kaffa zone of Ethiopia. *Cleaner and Responsible Consumption*, *12*, 100161. https://doi.org/https://doi.org/10.1016/j.clrc.2023.100161

Suárez, C. A., Guaño, W. A., Pérez, C. C., & Roa-López, H. (2024). Multi-objective optimization for perishable product dispatch in a FEFO system for a food bank single warehouse. *Operations Research Perspectives*, *12*, 100304. https://doi.org/https://doi.org/10.1016/j.orp.2024.100304

Suryana, A. (2014). Menuju Ketahanan Pangan Indonesia Berkelanjutan 2025 : Tantangan dan Penanganannya. *Forum Penelitian Agro Ekonomi*, *32*(2), 123–135. https://doi.org/http://dx.doi.org/10.21082/fae.v32n2.2014.123-135

Ty, T. Van, Minh, H. V. T., Avtar, R., Kumar, P., Hiep, H. Van, & Kurasaki, M. (2021). Spatiotemporal Variations in Groundwater Levels and the Impact on Land Subsidence in CanTho, Vietnam. *Groundwater for Sustainable Development*, *15*, 100680. https://doi.org/https://doi.org/10.1016/j.gsd.2021.100680

Walls, H., Baker, P., Chirwa, E., & Hawkins, B. (2019). Food Security, Food Safety & Healthy Nutrition: Are They Compatible? *Global Food Security*, *21*, 69–71. https://doi.org/10.1016/j.gfs.2019.05.005

Wang, K., Mirosa, M., Hou, Y., & Bremer, P. (2025). Advancing food safety behavior with AI: Innovations and opportunities in the food manufacturing sector. *Trends in Food Science & Technology*, *161*, 105050. https://doi.org/https://doi.org/10.1016/j.tifs.2025.105050

Wright, T., & Meylinah, S. (2017). *USDA Foreign Agricultural Service Global Agricultural Information Network (GAIN) Report 13 April 2017*. https://gain.fas.usda.gov/Recent GAIN Publications/Sugar Annual_Jakarta_Indonesia_4-13-2017.pdf

Yamaguchi, M., Praditsorn, P., Purnamasari, S. D., Sranacharoenpong, K., Arai, Y., Sundermeir, S., Gittelsohn, J., Hadi, H., & Nishi, N. (2022). Measures of Perceived Neighborhood Food Environments and Dietary Habits: A Systematic Review of Methods and Associations. *Nutrients*, *14*. https://doi.org/10.3390/nu14091788

Zaman, S. I., Khan, S., Zaman, S. A. A., & Khan, S. A. (2023). A grey decision-making trial and evaluation laboratory model for digital warehouse management in supply chain networks. *Decision Analytics Journal*, *8*, 100293. https://doi.org/https://doi.org/10.1016/j.dajour.2023.100293