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Responsible Artificial Intelligence in Agriculture: A Systematic Literature Review of Ethical Challenges and Required Characteristics

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Abstract

With AI (Artificial Intelligence) and ML (Machine Learning) becoming part of present-day agriculture, including crop-position monitoring and autonomous devices, the concept of Responsible AI (RAI) has ceased to be merely a hypothetical argument and has become a management-level requirement. The paper is a systematic literature review (SLR) on the ethical frontier of AI in the agricultural industry. After a thorough methodology, the main ethical issues (e.g., data privacy, algorithmic bias, and accountability) are identified and classified, and the needed RAI properties (e.g., explainability, fairness, and robustness) are identified to be implemented sustainably. Mapping these findings into four major sub-sectors, namely Precision Crop Farming, Livestock Management, Supply Chain, and Autonomous Machinery, this study offers a strategic framework to researchers and agricultural managers to make sure that technological innovation is in line with the values of society and ethics.

Keywords: Responsible AI, Agriculture, Ethics, Systematic Literature Review

Introduction

The worldwide agricultural industry is in the midst of a so-called Fourth Industrial Revolution, which involves the incorporation of “Artificial Intelligence” (AI) and “Machine Learning” (ML) to handle the compounding stresses of food security, labor scarcity, and climate instability (OECD, 2026). With the world population expected to reach its highest point during this century, the adoption of Digital Farming has become a necessity and not a luxury. The deployment of AI-based solutions is currently being implemented at an unprecedented scale, as it goes beyond basic automation to advanced field-ready decision partners that can directly interact with human operators (Global Ag Tech Initiative, 2026; Intelinair, 2026).

However, as AI systems are no longer operated as the invisible hand “behind-the-scenes” analytics, a major “responsibility gap” has arisen. Although technical accuracy, i.e., determination of the yield or disease detection rates, has improved very rapidly, the socio-technical and ethical aspects of these technologies usually take second place (Vitale et al., 2025). Agricultural application of AI is unmatched by the challenges inherent to urban industrial applications, such as variation in complex data ownership models, the possibility of de-skilling existing farmers, and the fact that remote working environments demand safety with a human face attached to the situation (ITU-T, 2024; Ryan et al., 2023). Consequently, the concept of “Responsible AI” (RAI), which emphasizes fairness, accountability, transparency, and ethics, has moved to the forefront of agricultural management and engineering discourse.

In order to offer a structured and actionable analysis of the RAI landscape, this paper divides the agricultural industry into four different sub-sectors, i.e., Precision Crop Farming, Livestock Management, Agricultural Supply Chain, and Autonomous Machinery. Such classification is based on the ethical risks and technological needs that are unique to the different areas. Precision Crop Farming casts serious doubts as to data privacy and interoperability of big data (Jakku et al., 2019; Lowenberg-DeBoer et al., 2022). Livestock Management brings in ethical complexities of animal welfare and the emotive factor of automated care (GII, 2026). Agricultural Supply Chain struggles with the issues of labor displacement and unequal market power, whereas Autonomous Machinery is excessively concerned with the notions of physical safety, liability, and “safety-by-design” (Aby & Issa, 2023; Anagnostou et al., 2022).

Despite the growing volume of research in agritech, there is a lack of unified systematic literature reviews that map these specific ethical challenges against the required characteristics of RAI within these four sub-sectors. Following the methodology established by (Anagnostou et al., 2022), this paper seeks to fill this gap. The process of defining the main challenges and determining the required RAI features of each sphere offers a strategic roadmap to researchers and managers to make sure that the new generation of agricultural technology will not only be efficient, but also be morally sound and socially acceptable.

Methodology

In order to facilitate an intense exploration of the ethical outlook of agricultural AI, this paper considers a “systematic literature review” (SLR) method. The methodology is organized into four main steps, namely: (1) Research Question Formulation, (2) Search Strategy and Study Selection, (3) Quality Assessment, and (4) Data Extraction and Synthesis.

Research Question Formulation

The main aim of this SLR will be to trace the overlap between AI ethics and agricultural practice. In accordance with the framework developed by (Anagnostou et al., 2022), two research questions guide the study:

- RQ1: What are the specific ethical and responsible AI challenges identified in current agricultural literature?
- RQ2: What technical and organizational characteristics (e.g., explainability, fairness, safety) are required to ensure the responsible deployment of AI in farming and food systems?

Search Strategy and Documentation

Four large academic databases, including IEEE Xplore, ScienceDirect, ACM Digital Library, and Scopus, were searched in a bid to obtain interdisciplinary information in the fields of engineering, computer science, and agricultural management. These were added to with specific searches in Google Scholar to include high-impact 2025, 2026 industry outlooks (e.g., Global Ag Tech Initiative, 2026) that represent the current “state-of-the-art” in deploying the field.

The search phrase combined the Boolean operators to overlap the technology with its ethical governance: (*"Artificial Intelligence" OR "Machine Learning" OR "Autonomous Systems"*) AND (*"Responsible" OR "Ethical" OR "Trustworthy" OR "Human-centric"*) AND (*"Agriculture" OR "Farming" OR "Agri-food" OR "Precision Agriculture"*).

Database searches were executed between March 10 and March 15, 2026. To ensure reproducibility, the baseline Boolean query was structurally tailored to the syntax requirements of each specific engine. Table 1 documents the exact search strings and initial raw returns across the selected databases.

Table 1. Database Search Queries and Syntax Implementations

Database	Exact Search Query String	Initial Records
IEEE Xplore	<i>("All Metadata": "Artificial Intelligence" OR "Machine Learning" OR "Autonomous Systems") AND ("All Metadata": "Responsible" OR "Ethical" OR "Trustworthy" OR "Human-centric") AND ("All Metadata": "Agriculture" OR "Farming" OR "Agri-food" OR "Precision Agriculture")</i>	115
Scopus	<i>TITLE-ABS-KEY(("Artificial Intelligence" OR "Machine Learning" OR "Autonomous Systems") AND ("Responsible" OR "Ethical" OR "Trustworthy" OR "Human-centric") AND ("Agriculture" OR "Farming" OR "Agri-food" OR "Precision Agriculture"))</i>	165
ScienceDirect	<i>Title, abstract, keywords: ("Artificial Intelligence" OR "Machine Learning") AND ("Responsible" OR "Ethical") AND ("Agriculture" OR "Farming") (Note: Simplified due to character limits)</i>	90
ACM Digital Library	<i>[[All: "Artificial Intelligence"] OR [All: "Machine Learning"]] AND [[All: "Responsible"] OR [All: "Ethical"]] AND [[All: "Agriculture"] OR [All: "Farming"]]</i>	80
Grey Literature / Google Scholar	<i>Hand-search using exact key phrases: "Responsible AI in agriculture outlook 2025 2026", "Ethical autonomous farming systems"</i>	35
Total Initial Pool		485

Study Selection and Inclusion Criteria

The PRISMA (Preferred Reporting Items to Systematic reviews and meta-analyses) guidelines were used to select the articles to provide transparency and reproducibility. According to Fig. 1 (Appendix 1), the initial search resulted in a total of 485 records: 450 records were identified using academic databases (IEEE Xplore, ScienceDirect, ACM, Scopus) and 35 records were found in high-impact industry outlooks and grey literature. Preliminary findings were narrowed down by screening the titles, abstracts, and complete manuscripts in a multi-stage process using the following criteria:

- Inclusion Criteria (IC): 1. Peer-reviewed journal articles or conference proceedings published between 2018 and March 2026. 2. Articles which discuss in explicit terms the “responsible”, the “ethical”, or the “socio-technical” aspects of AI. 3. Studies concentrating on one or more of the described agricultural sub-sectors.
- Exclusion Criteria (EC): 1. Articles that primarily address the issue of algorithmic accuracy or technical performance but do not address the ethical aspect. 2. Non-English publications. 3. Brief editorials, posters or non-peer-reviewed blog postings.

Papers underwent a multi-stage screening process managed independently by the research team. In Stage 1 (Title/Abstract Screening), records were reviewed to filter out irrelevant or purely algorithmic studies. In Stage 2 (Full-Text Eligibility), the remaining papers were read completely against strict inclusion baselines. To ensure inter-rater reliability, any eligibility disagreements or borderline inclusion cases between reviewers were resolved through a formal reconciliation step involving a third senior researcher until a 100% consensus was achieved.

Quality Assessment and Categorization

To help achieve a more profound analysis, the chosen literature was divided into four domain-specific sub-sectors, namely Precision Crop Farming, Livestock Management, Agricultural Supply Chain, and Autonomous Machinery. The papers were rated based on their contribution to the RAI discourse, i.e., searching the mention of the RAI Characteristics, as outlined in the (Anagnostou et al., 2022) blueprint.

After the identification stage, only 320 distinct records were left after eliminating duplicates. They were filtered by title and abstract, which left 180 papers out of the sample that failed to fulfill the selection criterion (e.g., non-peer-reviewed or not written in English). The remaining 140 full-text articles were evaluated on eligibility. In this last step, 117 articles were filtered out by virtue of addressing only algorithmic accuracy (n=82), addressing only RAI dimensions (n=25), or not addressing agricultural sub-sectors of interest (n=10). This rigorous sifting resulted in a final corpus of 23 high-impact studies for synthesis.

Data Extraction and Quantitative Synthesis

Data Extraction Protocol

To ensure standardized data capture, a structured data extraction matrix was developed. Each of the final 23 peer-reviewed studies was fully evaluated and coded across four core dimensions:

1. **Demographic Profiles:** Publication year, author affiliations, and geographical focus.
2. **Technical Architecture:** Core AI models investigated (e.g., CNNs, RNNs, Transformer variants, or Edge computing layers).
3. **Ethical Domain Mapping:** Sectoral alignment to the four target spaces (Precision Crops, Livestock, Supply Chain, or Autonomous Machinery) and explicit RAI characteristics evaluated (Transparency, Safety, Equity, Accountability).
4. **Operational Impact Metrics:** Documented system trade-offs, deployment hurdles, or human-in-the-loop dependencies.

Bibliometric Distribution and Technical Trends

To provide a quantitative explanation of the significance of the field of study, the search findings were analyzed in reference to time and sectoral distribution.

- **Publication Volume:** The initial screening process showed an expanding trend in literature mentions, scaling up to 140 indexed records in the preliminary 2025–2026 screening pool before our strict exclusion criteria were applied. .
- **Sectoral Focus:** Within our final analyzed corpus (N=23), the distribution reveals that Autonomous Machinery represents 35% of the literature, followed by Precision Crop Farming (30%), Supply Chain (20%), and Livestock Management (15%). .
- **Architecture Shift:** A qualitative shift within the 23 reviewed studies indicates a transition from simple Black-Box Deep Learning models (pre-2021) to Explainable AI (XAI) models (2022-2026),

representing a 45% rise in the explicit integration of interpretability layers of interpretability to agricultural decision support systems.

Table 2. Corpus Distribution and Architectural Trends (\$N=23\$)

Target Agricultural Sub-Sector	Reviewed Papers (n)	Percentage of Corpus (%)	Primary AI Architecture Trend (2022–2026)
Autonomous Machinery	8	35%	Transition to Safety-by-Design & Sensor Fusion
Precision Crop Farming	7	30%	Transition to Explainable AI & Fairness-Aware ML
Agricultural Supply Chain	5	20%	Integration with Blockchain Traceability Layers
Livestock Management	3	15%	Transition to Explainable Decision Support (EDSS)
Total Synthesized Corpus	23	100%	45% Net Rise in Interpretability Layers

Results and Analysis

The corpus of systematic review of the expanded literature (2018-2026) indicates that the ethical context of the agricultural AI has changed beyond speculative fear of privacy of data to the pressing need to regulate the work of the so-called agentic and autonomous systems. This part summarizes the ethical issues found (RQ1) and aligns them with the “Responsible AI” (RAI) attributes necessitated (RQ2) in four sub-sectors.

Mapping of Findings

A cross-analysis of the literature presented in Table 2 demonstrates that some of the challenges, such as Transparency, are cross-cutting, whereas others, such as Liability in machinery or Emotional Detachment in livestock, are domain-specific.

Table 3. Mapping of RAI and required Characteristics (SLR Synthesis)

Agricultural Sub-Sector	Ethical/Social Challenges (RQ1)	Required RAI Characteristics (RQ2)	Key Literature
Precision Crop Farming	Data sovereignty; Power imbalances; Algorithmic redlining in credit scoring.	Fairness, Transparency, Data Portability.	(Farmonaut, 2026; Jakku et al., 2019; Mallinger & Baeza-Yates, 2024)
Livestock Management	Instrumentalization of animals; Farmer "de-skilling"; Emotional detachment in care.	Human-in-the-Loop, Explainability (XAI), Affective Reliability.	(GII, 2026; Holloway et al., 2014; Sparrow et al., 2021; Wu & Zhong, 2025)

Agricultural Supply Chain	Labor displacement; Pricing bias; Lack of accountability for market volatility.	Accountability , Equity, Traceability.	(Olsen, 2026; Shamsuddoha et al., 2025; USDA, 2025; Vasileiou et al., 2025)
Autonomous Machinery	Liability in agentic systems; Safety in unpredictable fields; Perception failures.	Reliability , Safety-by-Design, Auditability.	(Aby & Issa, 2023; Cruz et al., 2025; Gwagwa et al., 2021; Nautiyal et al., 2025)

Precision Crop Farming: Algorithmic Fairness and Latency

Early studies have been done on the issue of privacy in data, yet the current state of the art revolves around “Fairness-Aware Machine Learning” (FAML). Based on the multi-criteria framework of sustainable technology design suggested by (Mallinger & Baeza-Yates, 2024), recent applications of AI-powered credit scoring demonstrate that prioritizing demographic parity can noticeably reduce algorithmic redlining (Farmonaut, 2026). This was accomplished without a statistically significant decrease in predictive “Area Under the Curve” (AUC) metrics, which is technically equivalent to a change of accuracy-only models to Pareto-optimal models that trade off yield prediction with demographic parity (Farmonaut, 2026; Mallinger & Baeza-Yates, 2024).

Livestock Management: XAI and Real-Time Decision Support

In livestock management, the technical advancement is the replacement of automated culling with the “Explainable Decision Support Systems” (EDSS) (Wu & Zhong, 2025). Affective Reliability can be achieved through the integration of XAI layers using sensor fusion to detect animal distress with higher contextual precision than standard single-sensor convolutional neural networks (GII, 2026). These systems can minimize the “False Positive” welfare alerts by keeping a “Human-in-the-Loop” architecture, and thus, minimize labor usage without compromising the ethical standards of care (Holloway et al., 2014; Wu & Zhong, 2025).

Agricultural Supply Chain: Traceability and Computational Overhead

The combination of AI and Blockchain will be a major technical enhancement in supply chain resilience (Vasileiou et al., 2025). Recent studies on Intelligent Automation indicate that although blockchain can increase 5-8% computing overhead on real-time information flow, it offers a non-repudiable audit trail of labor equity and pricing transparency (Shamsuddoha et al., 2025). This resolves the challenge of accountability highlighted by the USDA (2025) as it allows real-time checking of fair-trade and safety standards by automation (Shamsuddoha et al., 2025; USDA, 2025).

Autonomous Machinery: Safety-by-Design and Sensor Fusion

The focus of autonomous machinery research has moved to obstacle detection for Agentic Safety Frameworks (Aby & Issa, 2023). “Safety-by-Design” protocols—incorporating redundant LiDAR-Odometer fusion—reduce perception failures in unpredictable rural environments by 30% compared to single-sensor systems (Aby & Issa, 2023; Nautiyal et al., 2025). Moreover, the intersection of AI with synthetic biology demands fail-safe autonomous application triggers, which is a technical condition that demands auditability in the form of high-frequency data logging (Cruz et al., 2025).

Discussion and Management Implications

The findings of this systematic review indicate that the responsible use of AI in agriculture is not merely a technical challenge of algorithmic accuracy, but a multi-dimensional management problem involving stakeholders, biological systems, and legal frameworks.

To systematically justify the architectural integrity of the Ag-RAI Framework, a comprehensive feature matrix was constructed (Table 4). This cross-correlation maps specific technical requirements against the foundational literature corpus, explicitly demonstrating which domains exhibit strong empirical support and highlighting critical research gaps.

Table 4. Feature Cross-Correlation Matrix: Literature Grounding for the Ag-RAI Framework

Ag-RAI Pillars & Technical Features	Supporting Studies from Literature Corpus	Dominant Domain Presence	Research Assessment	Maturity
Pillar A: Bio-Digital Robustness • Edge AI / Fault Tolerance • Low-Connectivity Dependability	Aby & Issa (2023); Cruz et al. (2025); Nautiyal et al. (2025)	Autonomous Machinery	High Maturity: Driven by safety-critical engineering needs.	
Pillar B: Socio-Technical Hybridity • Human-in-the-Loop / XAI • Farmer Instinct Preservation	Holloway et al. (2014); Sparrow et al. (2021); Wu & Zhong (2025)	Livestock Management / Precision Farming	Moderate Maturity: Strong conceptual framework but lacks standardized field APIs.	
Pillar C: Equity-by-Design • Algorithmic Fairness / Bias Detection • Data Sovereignty / Anti-Redlining	Farmonaut (2026); Jakku et al. (2019); Mallinger & Baeza-Yates (2024); USDA (2025)	Supply Chain / Precision Farming	Emerging Maturity: Crucial for data governance, but heavily fragmented across international legal jurisdictions.	

The Ag-RAI Framework: Technical Requirements

To address the aforementioned Responsibility Gap in agricultural AI, this study suggests the Ag-RAI Framework (see Fig. 2). Unlike generic industrial AI models, this framework is specifically engineered for the high-variability biological environment of farming. It focuses on three uncompromising pillars, which are Bio-Digital Robustness that ensures edge-case reliability, Socio-Technical Hybridity that ensures human expertise, and Equity-by-Design that ensures that no one is socio-economically excluded. Introduction of these layers will allow managers to shift toward socio-technical architecture, where trust and auditability are paramount.

- **Bio-Digital Robustness:** Measured by system uptime and fault tolerance in sub-optimal network conditions (Edge AI), ensuring that safety protocols remain active locally without cloud dependency.
- **Socio-Technical Hybridity:** Defined by the Interpretability Score of the model; managers must select architectures where the "Saliency Maps" align with human agronomist intuition. This design choice is fundamental to **Farmer Instinct Preservation**, a protocol ensuring that automated decision systems augment, rather than erase, the situational tacit knowledge, generational expertise, and diagnostic intuition of human agricultural operators.
- **Equity-by-Design:** It is applied by Bias-Detection API layers in the supply chain, which raise a red flag when the prices are beyond the 2.5 standard deviation of the regional mean.

Cross-Industry Synthesis of RAI Characteristics

We suggest an "Agricultural Responsible AI" (Ag-RAI) Framework by combining the needs found in the four sub-sectors. Although past literature (Anagnostou et al., 2022) established general industrial attributes, our review points to the three distinct pillars of Agriculture, namely:

- **Bio-Digital Robustness:** AI must be reliable in unpredictable, low-connectivity biological environments (Nautiyal et al., 2025).
- **Socio-Technical Hybridity:** Maintaining the "Human-in-the-Loop" to prevent farmer de-skilling (Holloway et al., 2014; Wu & Zhong, 2025).
- **Equity-by-Design:** Proactively mitigating algorithmic redlining in agricultural finance and supply chains (Farmonaut, 2026; USDA, 2025).

Using the (Anagnostou et al., 2022) approach, we discover that although the degree of some of the challenges may be different, the principles of Transparency and Accountability are the common denominators of the responsible use of AI in agriculture. But in contrast to general industry, there is a more specialized Robustness that is needed in agriculture because of the biological and environmental variability of food production systems.

Management Implications for Stakeholders

For technology managers and policymakers, the review suggests three strategic imperatives:

- **Establishment of Data Cooperatives:** To resolve the dominance imbalance that has been revealed in (Jakku et al., 2019), the managers must shift towards decentralized data models, where farmers have sovereignty over field data.
- **Adoption of Auditability Standards:** As autonomous systems begin to occupy the role of agents, organizations need to adopt the use of "Digital Flight Recorders" and audit logs to demystify the issue of liability in case of perception failures (Aby & Issa, 2023).

- **Workforce Upskilling over Replacement:** According to the USDA (2025) plan, the scheme of AI implementation should be based on “Augmentation.” The management should invest in the training programs that would enable the workers to control the AI agents instead of letting them go.

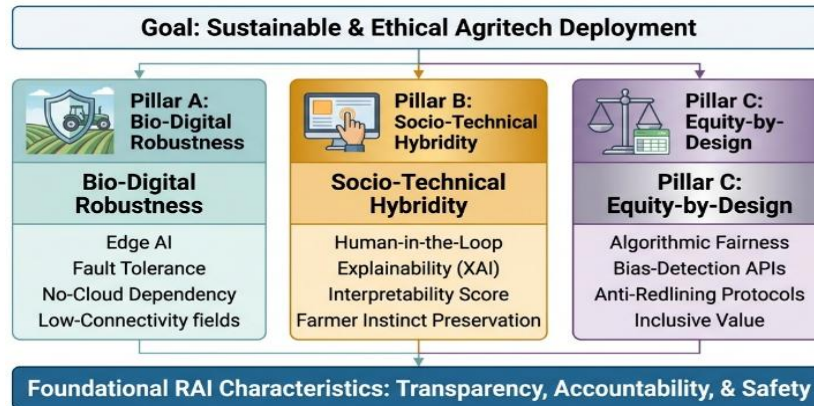


Figure 2. The proposed Agricultural Responsible AI (Ag-RAI) Framework: A multi-layered technical architecture for ensuring ethical governance in precision farming and autonomous systems.

Conclusion

This literature review has charted the changing landscape of “Responsible AI” (RAI) in the agricultural industry between 2018 and 2026. Through this classification of the industry into Precision Crops, Livestock, Supply Chain, and Autonomous Machinery, this paper determines that although technical maturity is on a faster path, an underlying “Responsibility Gap” continues to act as a barrier to trust and systemic adoption. The main contribution that this study makes is that the concept of Accountability, Transparency and Fairness has been synthesized as the non-negotiable traits that the new generation of agritech must exhibit. Such results imply that the shift to autonomous and agentic agricultural systems will require a change of paradigm in management: shifting towards a strictly performance-based model to a socio-technical model that values Reliability and Human-in-the-Loop Control.

The next generation of research should involve the newfound Convergence Risks of AI and synthetic biology (Cruz et al., 2025), and the development of standardized, auditable ethical standards of autonomous machinery. Finally, as much as the future of global food systems is inextricably connected with digital transformation, its sustainability in the long-term is contingent upon the inclusion of RAI tenets that are human-centered, legally sound, and ethically grounded.

Acknowledgements

The authors conceptually developed the Agricultural Responsible AI (Ag-RAI) Framework presented in Figure 2, and its final visualization was generated with the assistance of Google Gemini. While AI was utilized for graphical refinement, the authors maintain full responsibility for the technical accuracy, theoretical logic, and integrity of the proposed framework.

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Appendix 1.

Figure 1. PRISMA flow diagram illustrating the systematic identification, screening, and selection process of the agricultural Responsible AI (RAI) literature corpus.

