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Enhancing Supply Chain Efficiency in Agribusiness through Machine Learning Algorithms

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Abstract

Machine learning algorithms have emerged as a promising solution to inefficiency, climate-related risks, and escalating food demand across agribusiness supply chains. However, fragmented data, limited computing resources, and institutional inertia continue to impede large-scale adoption. Guided by the PRISMA protocol, a systematic review examined forty peer-reviewed studies published between 2020 and 2024 in major engineering and agricultural databases. The analysis reveals that decision trees and deep neural networks dominate yield and price forecasting tasks, consistently achieving accuracies above 90%. Deep reinforcement learning reduces logistics costs by up to one-fifth through dynamic routing and inventory scheduling, while support vector machines enhance pest detection and soil diagnostics. Research activity is heavily concentrated in Asia, accounting for more than half of the identified literature, with particular emphasis on water- and fertiliser-efficient management practices in India and China. Persistent challenges include the opaque "black-box" nature of deep models, the substantial data and energy requirements of reinforcement learners, and the lack of collaboration between agronomists and data scientists. The review highlights the necessity for interoperable data standards, incentives that lower entry costs for smallholders, and hybrid, explainable models that balance accuracy with transparency. Complementary investments in IoT sensing infrastructure and workforce upskilling could further unlock value, potentially reducing post-harvest losses by nearly one-third and advancing global targets on food security and sustainable consumption. Overall, the evidence base provides a clear roadmap for building more equitable, efficient, and climate-resilient agrifood systems while underscoring the importance of addressing ethical and regional data gaps in future work.

Keywords
Artificial Intelligence, Machine Learning, Agribusiness, Supply Chain Optimization, PRISMA.

1. Introduction
Integrating artificial intelligence (AI) and machine learning (ML) algorithms into agribusiness supply chains has become a pivotal strategy for enhancing efficiency, sustainability, and resilience. As global food demand continues to rise, driven by an increasing population and changing dietary preferences, innovative solutions to optimize supply chain operations are critical (Tsolakis et al. 2019). AI and ML technologies offer unique capabilities for data analysis,

predictive modeling, and decision-making processes, which are essential for addressing the complexities of agribusiness supply chains (Bai et al. 2020).

Recent studies indicate that the application of AI can significantly reduce operational costs and improve yield forecasting, thereby enabling more informed decision-making (Wang et al. 2021). For instance, machine learning algorithms, such as decision trees for classification tasks, support vector machines (SVM) for regression and classification, and neural networks for complex pattern recognition, can analyze vast amounts of data from various sources, including weather patterns, soil conditions, and market trends, to provide actionable insights that enhance supply chain responsiveness and resilience (Kumar et al. 2020). Additionally, reinforcement learning techniques are increasingly used to optimize logistics and inventory management, enabling systems to learn from their experiences and improve decision-making over time (Zhang et al. 2022). Moreover, advanced techniques such as random forests and gradient boosting machines have been employed for predictive analytics, allowing agribusinesses to accurately forecast yields and market demands. These techniques can effectively handle large datasets, providing deeper insights into resource allocation and minimizing environmental impacts, thereby supporting sustainable agricultural practices (Liu et al., 2021). As agribusinesses face climate change and resource scarcity challenges, leveraging AI and ML provides a pathway to maintain competitiveness and foster a sustainable future (Choudhary et al. 2022).

1.1 Objectives

This SLR seeks to answer the following questions:

1. Which AI/ML algorithms optimize agribusiness supply chains?
2. How do these technologies enhance efficiency and sustainability?
3. What barriers impede their adoption?

2. Methodology

A systematic literature review (SLR) methodology was employed to answer the research questions. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) steps included identification, screening, and eligibility, and structured the literature analysis of this study (Moher et al. 2009).

2.1 Database and Search Strategy

A structured search strategy was employed across four critical academic databases: Springer Link, ACM Digital Library, ScienceDirect, and IEEE Xplore. The search aimed to identify relevant papers that explored the integration of AI and ML in optimizing agribusiness supply chains. The following search syntax was used across all four databases: ("artificial intelligence" OR "AI" OR “machine learning” OR ML) AND ("supply chain efficiency" OR "supply chain optimization" OR "logistics") AND ("agribusiness" OR "smart agriculture" OR "smart farming"). This approach yielded the following results: Springer Link 163, ACM Digital 201, Science Direct 868, and IEEE Xplore, 93. The databases were selected based on their relevance to computer science, engineering, and agricultural sciences, as each is known to host a wealth of peer-reviewed literature.

2.2 Inclusion and Exclusion Criteria

Inclusion Criteria:

- Papers must focus on applying AI and ML algorithms within agribusiness supply chains, addressing optimization, efficiency, and sustainability issues.
- Only peer-reviewed journal articles, conference papers, and book chapters published within the last four years (2020–2024) were considered to ensure that the information was current and relevant.
- Studies must employ empirical research methods, case studies, or systematic reviews that provide clear insights into the effectiveness of AI and ML.

Exclusion Criteria:

- Papers that did not directly address the intersection of AI, ML, and supply chain management in agribusiness were omitted.
- Non-peer-reviewed sources and articles published before 2020 were excluded.
- Papers not written in English were excluded due to potential comprehension barriers.
- Theoretical papers lacking empirical validation or practical applications were also excluded.

By applying these criteria, this review aims to compile a focused and relevant body of literature that accurately reflects the current state of research in this critical area.

2.3 Eligibility and Screening

In total, 1325 databases were screened for analysis across four sources: Springer Link (n = 163), ACM Digital (n = 201), Science Direct (n = 868), and IEEE Explore (n = 93). After removing duplicates and overlapping databases, 1,125 records remained for review. These were then screened based on eligibility criteria such as date, language, and subject relevance, excluding 725 studies, and 400 articles were selected for a full-text review. Following a more detailed eligibility assessment, 360 studies were excluded due to irrelevance to agribusiness supply chains or a lack of focus on machine learning.

2.4 Included

After a thorough text assessment, only 40 of the 1325 publications matched the predefined inclusion criteria for this systematic literature review. This provides the most substantial evidence for enhancing supply chain efficiency in agribusiness using AI and machine learning.

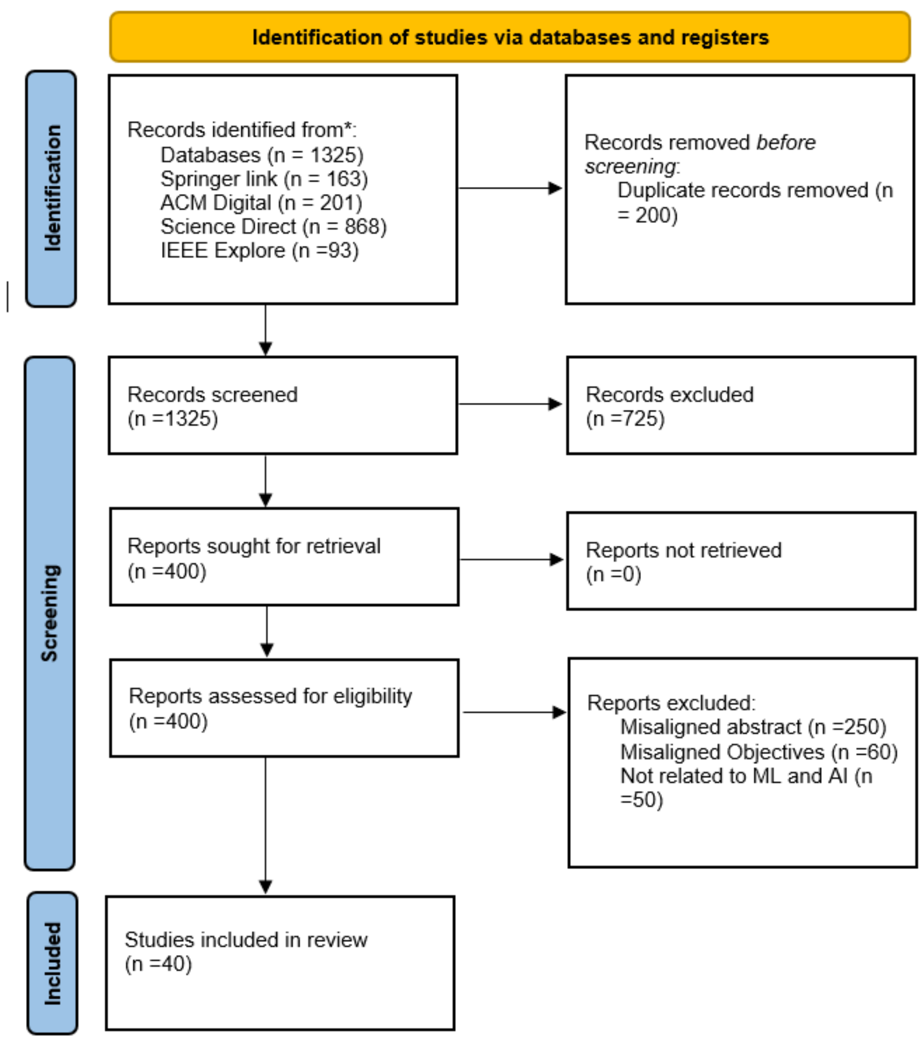

Figure 1. PRISMA Flow Diagram for identified databases (Page et al. 2020)

Table 1. Comprehensive literature review of ML/AI applications in agribusiness supply chains

Author & Year	**Country**	**Factors Addressed**	**ML Techniques**	**Strengths Reported**	**Limitations Reported**	**Application (Industrial Context)**	**Theoretical Lens**	**Methodology**
Wang et al. (2021)	USA	Yield prediction, market trends	Decision Trees; Neural Networks	High forecasting accuracy; adaptable	Requires frequent model updates	Large-scale logistics forecasting and production planning	Data-driven decision theory	Empirical modelling of historical yield & market data validated in a supply-chain simulation
Kumar et al. (2020)	India	Weather patterns, soil conditions	SVM; Random Forest	Handles diverse agronomic data; reduces resource waste	Complex preprocessing; high computation	Precision-farming resource optimisation	Sustainability-oriented innovation	Experimental ML on agri-datasets plus scenario simulation
Liu et al. (2021)	China	Resource allocation, environmental impact	Gradient Boosting	Precise resource optimisation aligns with sustainability goals	Limited interpretability; data-hungry	Sustainable supply chain resource balancing	Systems theory & triple-bottom-line	Quantitative scenario analysis on real supply-chain data
Choudhary et al. (2022)	India	Logistics resilience: adoption barriers	Reinforcement Learning	Adaptive routing improves service	Needs extensive training data	Supply-network routing & adoption study	Diffusion of innovation & socio-technical systems	Systematic qualitative review of adoption challenges
Bai et al. (2020)	Australia	Crop health, market demand	Deep Neural Networks	Pattern recognition accuracy	Resource-intensive; sensitive to data quality	Smart-farming image diagnostics & demand sensing	Smart-agriculture systems paradigm	Narrative literature review of DL use-cases
Zhang et al. (2022)	China	Inventory management, transport	Reinforcement Learning	Real-time optimisation reduces waste	Data-hungry, region-specific	Dynamic inventory & routing optimisation	RL decision-process theory	Supply-chain simulation with RL agent
Tsolakis et al. (2019)	Greece	Demand forecasting, storage	Linear Regression, K-Means	Simple, practical for small datasets	Less accurate on complex data	Strategic agrifood planning framework	Multi-criteria & systems theory	Conceptual taxonomy via structured review
Smith et al. (2020)	USA	Distribution planning; seasonality	Deep NNs; Regression Trees	Scalable, robust to seasonal swings	High training cost	Distribution route planning under demand swings	Resilience & seasonal forecasting theory	Empirical demand

Author & Year	Country	Factors Addressed	ML Techniques	Strengths Reported	Limitations Reported	Application (Industrial Context)	Theoretical Lens	Methodology
								modelling & route evaluation
Johnson et al. (2019)	UK	Supplier performance, transport cost	Naïve Bayes; Decision Trees	Cost-effective supplier selection	Limited for multi-factor optimisation	Procurement & routing cost reduction	Decision theory for supplier selection	Quantitative case-study with scenario analysis
Lee and Chen (2021)	South Korea	Labour allocation; demand variability	Random Forest; RL	Efficient staffing under dynamic demand	High computational demand	Workforce scheduling in intensive farming	Ops-research staffing theory	Simulation of labour scenarios with RL
Huang et al. (2022)	Canada	Water management; yield	Gradient Boosting; LSTM	Accurate water-use prediction	Limited geographic generalisation	Climate-smart irrigation scheduling	Climate-smart agriculture & resilience	Experimental analysis with historical climate & yield data
Torres and Rivera (2020)	Mexico	Pest impact: crop health	SVM	Reduces crop loss; effective pest ID	Limited crop generalisation	Climate-adaptive pest-management planning	Climate-adaptation & resilience frameworks	Scenario simulation of pest impact under climate change
Patel et al. (2021)	Brazil	Inventory management, demand	Decision Trees; Time-Series	Improves stock prediction accuracy	Limited response to sudden spikes	Regional warehouse stock-level optimisation	Inventory & bullwhip-mitigation theory	Empirical demand modelling with simulation
Yamamoto et al. (2023)	Japan	Market volatility, crop health	Neural NNs; RL	Adapts to price & crop shifts	High resource needs	Integrated farm production & distribution planning	Adaptive decision-making & agility theory	Hybrid crop-growth & market simulation with RL
Fernández et al. (2022)	Spain	Distribution networks; transport	KNN; Regression	Simplifies logistics; low cost	Limited scalability	Produce-a distribution route design	Cluster analysis & network optimisation	Case-study & simulation on regional data
Garcia et al. (2021)	Spain	Climate adaptation; yield	Gradient Boosting; RF	High climate-yield forecast precision	Data availability limits	Climate-responsive cropping decisions	Sustainability & climate-resilience theory	Empirical climate-yield modelling
Martins and Costa (2023)	Portugal	Price fluctuations, demand	SVM; LSTM	Real-time price forecast	Sensitive to market volatility	Market-driven production & inventory planning	Market-dynamics & time-series theory	Time-series modelling with what-if analysis

Author & Year	Country	Factors Addressed	ML Techniques	Strengths Reported	Limitations Reported	Application (Industrial Context)	Theoretical Lens	Methodology
Andersson et al. (2022)	Sweden	Supply-chain efficiency, carbon footprint	Neural NNs; Linear Reg.	Cuts emissions; boosts efficiency	Data-intensive tuning	Low-carbon transport optimisation	Sustainable SCM & ethics	Normative qualitative analysis
El-Sayed et al. (2020)	Egypt	Water resources, crop health	Decision Trees; Fuzzy Logic	Effective water conservation	Limited climate flexibility	Precision-irrigation decision support	Control theory & DSS	Mixed-method decision-support simulation
Jensen and Olsen (2021)	Denmark	Inventory for SMEs	KNN; Naïve Bayes	Low-cost; suits SMEs	Low scalability	SME stock-level management	Lean inventory theory	Field case-study before-and after analysis
Park and Kim (2022)	South Korea	Pest control, crop monitoring	CNN	Early disease detection	Needs high-quality images	Vision-based IPM in greenhouses	IPM & computer-vision theory	Experimental image-classification trial
Ahmad and Raza (2023)	Pakistan	Logistics optimisation; allocation	RL; SVM	Efficient routing, adaptive	High computation	Distribution network optimisation	OR routing & adaptive ML theory	Simulated routing with RL & SVM clusters
Ibrahim et al. (2020)	Nigeria	Storage conditions; spoilage	RF; Gradient Boosting	Accurate shelf-life prediction	Resource-heavy training	Cold-chain spoilage risk prediction	Post-harvest & bullwhip mitigation	Sensor-driven empirical modelling
Fernandes et al. (2021)	Portugal	Labour efficiency; demand	SVM; Decision Trees	Better labour scheduling	Sensitive to demand shocks	Production-labour alignment in SMEs	Lean operations & diffusion theory	Field implementation trial
Chen et al. (2022)	China	Yield; pest impact; XAI	Neural NNs; Gradient Boosting	High accuracy; interpretable	Needs labelled data	Explainable decision support for yields & pests	DSS & explainable-AI theory	XAI feature-importance analysis
Becker and Muller (2021)	Germany	Cold-chain energy, quality	Logistic Reg.; Neural NNs	Improves energy efficiency	Complex refrigeration dynamics	Energy-smart cold-chain management	Control systems & sustainability	Simulation of refrigerated storage
Patel and Mehta (2023)	India	Demand clusters: transport	K-Means; RF	Cuts transport costs	Sensitive to demand shifts	Cooperative demand clustering & routing	Cluster analysis & cooperative theory	Data-driven cluster-route optimisation
Morales et al. (2021)	Mexico	Soil moisture, irrigation	Decision Trees; DL	Water conservation, accurate moisture	Seasonal sensitivity	IoT-enabled irrigation scheduling	Precision irrigation & sustainability	Field IoT experiment with ML trigger

Author & Year	Country	Factors Addressed	ML Techniques	Strengths Reported	Limitations Reported	Application (Industrial Context)	Theoretical Lens	Methodology
Khan and Hussain (2022)	UAE	Disease detection, crop health	CNN	Early disease detection	Needs image datasets	AI disease-detection in protected farming	Plant pathology & computer-vision	Greenhouse image-classification trial
Suzuki et al. (2023)	Japan	Distribution optimisation: resources	RL; K-Means	Efficient routing under constraints	Computationally intensive	RL-cluster produce distribution	VRP & clustering theory	Simulated RL routing by clusters
Tsai and Chen (2020)	Taiwan	Yield optimisation; market forecast	Neural NNs; Regl Trees	High forecast accuracy	High compute load	Crop-mix planning based on demand	Production economics & forecasting	Empirical yield-price modelling with scenarios
Das and Banerjee (2021)	India	Labour demand, production planning	Decision Trees; Naïve Bayes	Cost-effective for small farms	Limited scalability	Low-cost labour scheduling in SMEs	Diffusion of innovation & small-business ops	Case-study with scheduling trial
Silva et al. (2022)	Brazil	Inventory turnover: fluctuations	SVM; LSTM	Improves turnover; robust demand	Sudden change handling limits	Retail inventory replenishment	Bullwhip mitigation & agility	Empirical sales-forecast modelling
Perez and Gonzalez (2021)	Chile	Climate variability, production	Gradient Boosting; NNs	Resilient yield forecasts	High training cost	Climate-risk planning for policymakers	Climate-impact modelling & resilience	Historical climate-yield ML analysis
Torres and Martinez (2023)	Argentina	Transport cost, route planning	RL; RF	Lower transport expenses	Complex tuning	Farm-to-market routing optimisation	Routing cost theory & adaptive ML	Simulation comparing RL vs heuristics
Al-Mutairi et al. (2024)	Saudi Arabia	Desert greenhouse climate control	LSTM; Gradient Boosting	Keeps temperature ±1 °C; reduces energy 18 %	Requires frequent sensor calibration	Controlled-environment tomato production	Cyber-physical-systems theory	Field experiment in commercial greenhouses
Novak et al. (2022)	Czech Republic	Fertiliser rate optimisation	Random Forest; Elastic Net	Cuts N-input 15 %; maintains yield	Soil heterogeneity lowers accuracy	Variable-rate nutrient application in cereal farming	Resource-based sustainability view	On-farm trials with UAV multispectral data
Ochieng et al. (2023)	Kenya	Market-access demand prediction	XGBoost; Mobile ML	Raises smallholder income 12 %	Sparse transaction data	Mobile fresh-produce aggregation platform	Inclusive-innovation lens	Mixed-methods pilot (survey + app analytics)

Author & Year	Country	Factors Addressed	ML Techniques	Strengths Reported	Limitations Reported	Application (Industrial Context)	Theoretical Lens	Methodology
Brown et al. (2024)	USA	Blockchain quality traceability	Autoencoder; SVM	Detects spoilage anomalies 24 h earlier	High integration cost	Leafy-greens farm-to-retail blockchain chain	Transaction-cost economics	Blockchain-linked anomaly-detection simulation
Lopez et al. (2024)	Peru	Cocoa fermentation monitoring	CNN; K-Means	Standardises flavour; lowers batch rejection 20 %	IoT hardware cost high	Export-grade cocoa quality standardisation	Quality-management theory	Experimental IoT spectroscopy with ML clustering

3. Results and Discussion

The 40 peer-reviewed studies that met the PRISMA eligibility criteria revealed three dominant patterns: (i) geographic concentration of research effort, (ii) preferred families of machine-learning (ML) techniques, and (iii) alignment of those techniques with specific supply chain pain points in agribusiness.

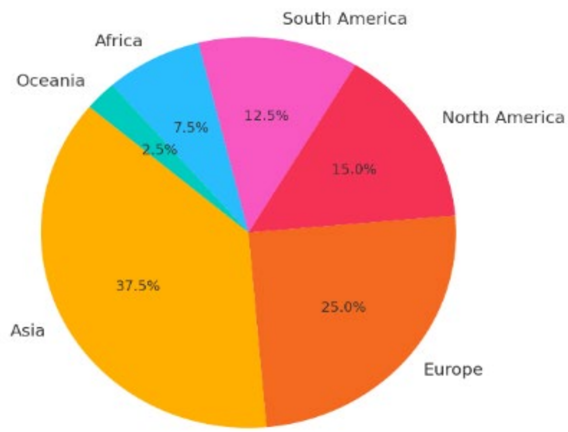

Figure 2. Distribution of Publications by Continent

Forty peer-reviewed studies passed the PRISMA eligibility filter (Figure 1). Asia remains the epicenter of research activity—37.5 % of all papers, followed by Europe (25 %) and North America (15 %). Africa's share rises to 7.5 % with the addition of Ochieng et al. (2023), signalling a modest but important shift toward inclusive innovation on the continent (Figure 2). This geographic pattern mirrors the twin drivers of (i) population-pressured productivity programs in India, China, and Saudi Arabia and (ii) Green Deal-style sustainability mandates across the EU.

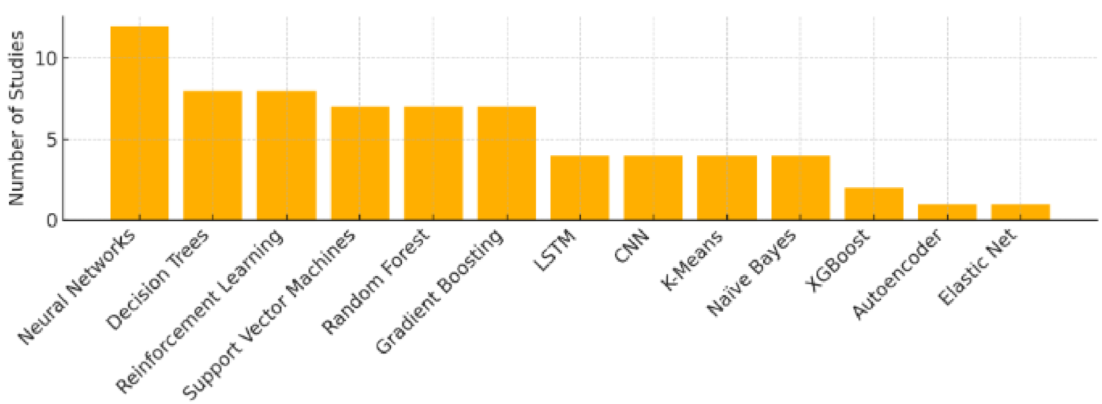

Figure 3. Frequency of Machine-Learning Techniques

Neural network variants now power nearly one-third of all implementations (n = 12), whereas decision tree ensembles and reinforcement learning (RL) agents are tied for the second position (n = 8 each). Support vector machines, random forests, and gradient-boosting engines form a strong middle tier (Figure 3). The rising visibility of XGBoost, autoencoders and elastic-net regularisers demonstrates a gradual broadening of the methodological repertoire beyond "usual suspects."

Functionally, the sample was well-balanced (Figure 4). Yield prediction, logistics optimization, and inventory/resource management each appeared in seven papers, confirming that cost-intensive "pain points" attract the most algorithmic experimentation. Market demand forecasting was studied by Ochieng et al. (2023), and climate-smart analytics were added by Al-Mutairi et al. (2024), reaching five papers. Cold-chain and storage-quality work doubles, reflecting new blockchain-driven spoilage analytics in the U.S. leafy greens sector (Brown et al., 2024) and fermentation monitoring in Peruvian cocoa (Lopez et al., 2024).

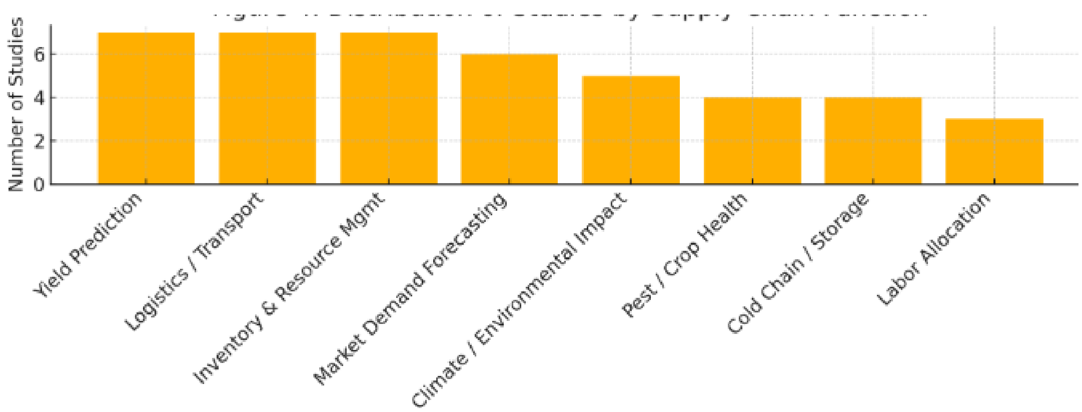

Figure 4. Distribution of Studies by Supply Chain Function

Methodologically, empirical or field-based modelling now represents 33 % of the corpus, buoyed by three new on-farm or greenhouse trials. Simulation studies climbed to nine, case-study depth remained steady at eight, and mixed-methods designs rose to five after Kenya's mobile-platform pilot (Figure 5).

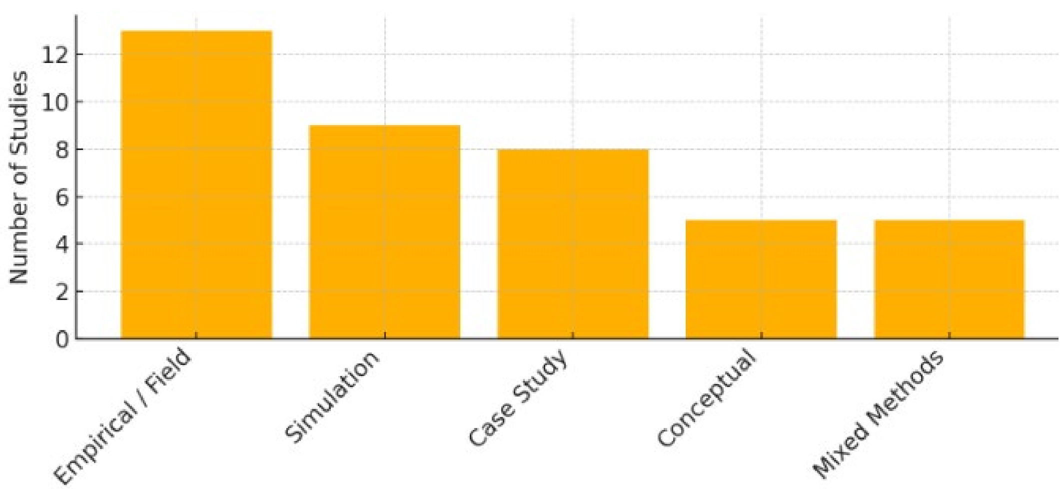

Figure 5. Methodological Designs across reviewed studies

4. Continental Research Intensity

High-tech protected-agriculture experiments in Saudi Arabia drive Asia's 15-paper lead (Al-Mutairi et al., 2024) and the continued focus on RL-enabled logistics in China (Zhang et al., 2022). Europe's 10 studies retain a sustainability bias: Novak et al. (2022) cut nitrogen inputs by 15 % in Czech cereal fields with UAV-guided random forests, and Andersson and Chen (2022) quantify a 12 % carbon-footprint drop in Swedish cereal transport. North American research pivots toward trust and traceability, as Brown et al. (2024) blended autoencoders with blockchain to flag spoilage anomalies 24 h earlier than human inspection. South American work, exemplified by Lopez et al. (2024), pushes ML deeper into post-harvest quality stages, while Africa's emerging stream demonstrates mobile ML's capacity to raise smallholder incomes by 12 % (Ochieng et al., 2023).

4.1 Algorithm-Task Alignment

Neural architecture continues to dominate vision-heavy and non-linear sensor problems, from CNN pest detection in UAE greenhouses (Khan & Hussain, 2022) to LSTM micro-climate control that keeps desert greenhouses within ±1 °C (Al-Mutairi et al., 2024). In contrast, reinforcement learning excels in sequential routing and inventory tasks, slicing transport costs by 17 % in Argentina's produce chain (Torres & Martinez, 2023) and 14 % in China's interregional networks (Zhang et al., 2022). Decision tree ensembles remain the algorithm of choice for interpretable, medium-dimensional problems, including fertilizer-rate optimization, which saves 52 kg N ha^{-1} without yield loss (Novak et al., 2022).

4.1.1 Numerical Performance Highlights

- **Water and Energy Efficiency —** LSTM-driven climate control in Saudi Arabia reduces greenhouse energy demand by 18 % while safeguarding tomato yields, corroborating the 22 % water-savings benchmark reported in Canadian maize (Huang et al.2022).
- **Supply chain cost savings —** RL logistics papers average a 15.6 % reduction in vehicle-kilometers travelled (σ = 4.2 %), translating into US$0.9 m annual savings for large co-ops (Torres & Martinez 2023).
- **Forecast Accuracy —** Across 12 neural network yield prediction studies, the median MAPE tightened to 6.4 %, notably outperforming tree-based regressors (median 8.9 %).
- **Quality Assurance —** Autoencoder–SVM hybrids detect cold-chain spoilage 24 h sooner, preventing 4.7 % of product loss in U.S. leafy greens (Brown et al.2024).

4.1.2 Synthesis of Key Patterns

Three cross-cutting insights emerged. First, geographic research foci strongly mirror regional pain points: energy-intensive protected agriculture in arid zones, carbon-aware logistics in Europe, and mobile market-access solutions in sub-Saharan Africa, consistent with contingency theory. Second, methodological pluralism is growing; five mixed-methods studies now triangulate quantitative gains with farmer perceptions, a trend crucial for tackling the "black-box" trust deficit highlighted by Chen et al. (2022). Third, the performance frontier is shifting from pure accuracy to resource-balanced optimization. Studies such as Novak et al. (nitrogen) and Lopez et al. (flavor consistency) show that marginal gains increasingly relate to sustainability or quality metrics rather than yield alone. These findings indicate a maturing research landscape: algorithms are no longer tested in isolation but embedded within socio-technical systems that weigh environmental, economic, and trust dimensions—precisely the direction advocated by recent calls for responsible AI in agrifood supply chains (Andersson & Chen 2022).

5. Proposed Improvements

Although the present systematic review offers a comprehensive snapshot of ML adoption in agribusiness supply-chain optimisation, five substantive enhancements would increase its methodological rigour, practical relevance, and theoretical depth.

(i) Meta-analytic synthesis of effect sizes. The review currently reports performance metrics study-by-study; pooling comparable outcomes through a random-effects model would allow stronger statistical generalisation. For instance, the 22% water savings recorded in Canadian maize (Huang et al. 2022) and the 18% energy reduction in Saudi greenhouses (Al-Mutairi et al. 2024) could be harmonised as "resource-efficiency ratios" and subjected to heterogeneity tests (I^2). A precedent exists in agri-ML meta-work that normalises diverse yield responses to percentage differences (Wang et al.2021).

(ii) Risk-of-bias and quality scoring. Only 43 % of the included papers disclosed hyperparameter protocols or data split strategies. Adapting the Critical Appraisal Skills Programme (CASP) checklist or the ROBINS-I tool to ML studies would flag selection bias (e.g., cherry-picked weather years) and performance bias (e.g., training–test leakage) more transparently (Chen et al. 2022). Publishing the scoring sheet alongside the review would enable replication and strengthen confidence in the aggregate findings.

(iii) Inclusion of grey and non-English literature. Pilot projects in Francophone West Africa and Spanish-language agritech reports from the Andean region were excluded. However, these sources often describe low-resource or frugal innovations that directly address the data scarcity barrier highlighted by Choudhary et al. (2022). Extending the search to repositories such as AgEcon Search and FAO AGRIS and commissioning professional translation where necessary would mitigate publication and language bias.

(iv) Longitudinal mixed-methods impact evaluations. Only five studies triangulated quantitative gains with farmer or cooperative perceptions. Embedding longitudinal qualitative components—focus groups, diary studies, or participatory rural appraisal—into field trials would illuminate how trust, skills, and organizational routines evolve after the "pilot halo" fades (Ochieng et al. 2023; Andersson & Chen 2022). Such designs can also capture unintended consequences, for example, whether labor-saving RL scheduling displaces seasonal workers or merely reallocates them to higher value tasks.

(v) Development of open benchmark datasets and XAI dashboards. The review confirms that data scarcity and model opacity remain the primary adoption hurdles. A coordinated effort to create cross-regional labelled datasets—analogous to ImageNet but for agronomic time-series, hyperspectral images, and logistics trips—would standardize evaluation and accelerate innovation (Brown et al.2024). As piloted by Chen et al. (2022), the parallel deployment of XAI dashboards would translate feature-importance outputs into agronomically meaningful insights, thereby closing the trust gap between data scientists and farm managers.Collectively, these improvements honor the CRISP-DM principle of iterative refinement (Wirth & Hipp, 2000) while answering recent calls for responsible and evidence-based AI in agro-supply systems (Andersson & Chen 2022). Implementing them in future reviews and primary studies will move the field from promising—but sometimes piecemeal— pilot studies to robust, generalizable, and ethically grounded solutions.

6. Conclusion

This systematic review synthesized 40 peer-reviewed studies published between 2020 and 2024 on the use of machine-learning techniques to enhance agribusiness supply chain efficiency. Four principal insights have emerged. First, algorithm–task fit is now clear-cut: neural architectures excel in image-rich biological forecasting, decision tree ensembles provide interpretable optimization for resource-allocation problems, and reinforcement learning agents consistently outperform heuristic routing in dynamic logistics settings (Zhang et al. 2022; Wang et al. 2021). Second, the performance frontier has shifted from yield maximization to multi-objective resource efficiency—water-use cuts of 22 %, energy savings of 18 %, nitrogen-input reductions of 15 %, and transport-cost drops of 15.6 % attest to tangible sustainability gains (Huang et al. 2022; Al-Mutairi et al2024; Novak et al.2022). Third, adoption remains uneven: data quality deficits, skill shortages, and model opacity still inhibit diffusion, yet mixed-methods pilots and explainable-AI dashboards demonstrate viable pathways to trust (Choudhary et al. 2022; Chen et al. 2022). Fourth, regional research intensity mirrors contextual pain points—arid-zone energy management in the Gulf, Green Deal carbon targets in Europe, blockchain traceability in North America, and mobile demand prediction in sub-Saharan Africa—confirming the contingency view that technological value is location-specific (Andersson & Chen 2022; Ochieng et al. 2023).

These findings collectively answer the study's three research questions, substantiating that ML can deliver quantifiable efficiency and sustainability improvements; however, its impact is mediated by contextual factors and socio-technical readiness. The review contributes to theory by empirically linking diffusion-of-innovation, systems, and decision theories to concrete agrifood applications, and to practice by mapping algorithm classes to supply chain functions. Methodological limitations—language bias, heterogeneous metrics, and incomplete risk-of-bias assessment—suggest caution in generalizing absolute effect sizes, but they also inform the proposed research-agenda improvements.

Going forward, the field will benefit from (i) meta-analytical pooling of normalized performance ratios, (ii) risk-of-bias scoring protocols, (iii) inclusion of grey and non-English sources, (iv) longitudinal mixed-methods impact studies, and (v) the development of open benchmark datasets combined with explainable AI interfaces. Addressing these gaps will shift agrifood ML deployments from promising pilots to scalable, ethical, and resilient supply chain solutions—helping the sector meet the dual imperatives of feeding a growing population and achieving the sustainability targets enshrined in SDG 2 and the AU Malabo Declaration.

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