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**STRATEGIC APPLICATION OF ARTIFICIAL INTELLIGENCE IN
AGRIBUSINESS SYSTEMS FOR MARKET EFFICIENCY AND
ZOOBOTIC RISK MITIGATION**

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Abstract

This study investigates the strategic application of artificial intelligence (AI) in agribusiness systems with the dual aim of enhancing market efficiency and mitigating zoonotic risks, addressing two of the most critical challenges confronting global food systems. AI has emerged as a transformative technological paradigm capable of integrating vast, heterogeneous datasets from agricultural production, supply chain logistics, and veterinary health networks to generate real-time, predictive insights. These capabilities hold significant potential to stabilize volatile markets and strengthen biosecurity within highly interconnected agri-food systems. To examine this potential systematically, the study employed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, which ensured methodological transparency, reproducibility, and rigor. An initial search retrieved 1,247 publications across major scholarly databases and institutional repositories. Following a structured screening and eligibility assessment process, 122 studies were selected for in-depth qualitative synthesis. These studies were thematically categorized into seven domains: conceptual and theoretical foundations; production-level optimization; market systems and supply chain efficiency; zoonotic risk detection and mitigation; global case studies and institutional experiences; data infrastructure, ethics, and governance; and synthesis of conceptual gaps. Simultaneously, AI enhances bio surveillance through anomaly detection, natural language processing of veterinary data, genomic epidemiology, and spatial risk modeling, enabling earlier detection and targeted containment of zoonotic threats. Evidence from global case studies highlights measurable improvements in yield stability, compliance reliability, and disease risk management, alongside reductions in losses and border clearance delays. The review also identifies critical enabling conditions—such as data interoperability, governance frameworks, and institutional capacity—that determine the long-term success of AI integration. Collectively, this synthesis reveals that AI can function as a unifying infrastructural layer that links efficiency and biosecurity goals, reframing them as mutually reinforcing rather than competing objectives. The study concludes that strategic AI deployment, underpinned by robust data systems and cross-sectoral governance, offers a viable pathway to building resilient, transparent, and risk-aware global agribusiness networks.

Keywords

Artificial Intelligence, Agribusiness Systems, Market Efficiency, Zoonotic Risk, Bio surveillance.

INTRODUCTION

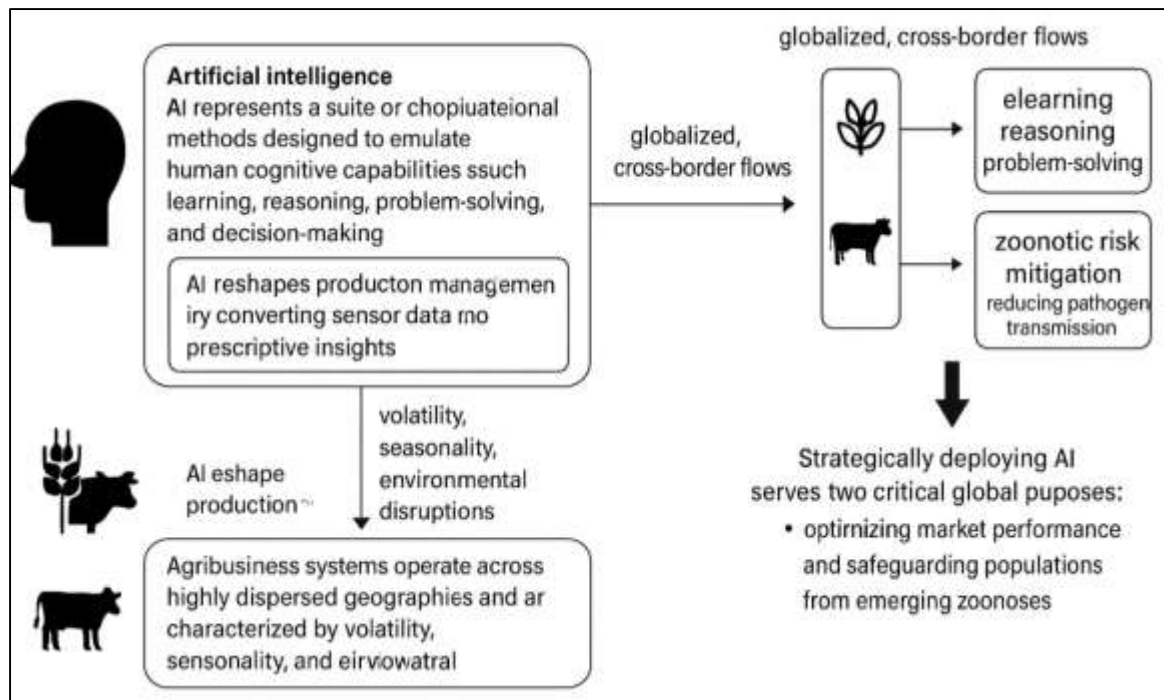
Artificial intelligence represents a suite of computational methods designed to emulate human cognitive capabilities such as learning, reasoning, problem-solving, and decision-making (Konar, 2018). Within the context of agribusiness systems, AI functions as an enabling infrastructure that enhances the efficiency, responsiveness, and resilience of complex supply chains spanning production, processing, distribution, and retailing. Agribusiness is inherently globalized, involving cross-border flows of inputs, commodities, and information, all of which require rapid, accurate decision-making to maintain competitive markets and safeguard public health. Market efficiency in this domain refers to the ability of agricultural markets to allocate resources optimally, reduce transaction costs, and ensure that prices accurately reflect the underlying conditions of supply (Siemens et al., 2022), demand, and quality. Zoonotic risk mitigation refers to the reduction of the probability and severity of pathogen transmission between animals and humans, particularly in environments where livestock production intersects with human consumption. Because agriculture is a primary interface where human activity overlaps with animal and environmental systems, it is a key site for both economic development and biosecurity concerns. Strategically deploying AI within these systems serves two critical global purposes: Kumar et al. (2025) optimizing market performance and safeguarding populations from emerging zoonoses. International organizations increasingly view these twin objectives as interdependent. Efficient markets reduce food insecurity and price shocks, while enhanced zoonotic surveillance reduces the likelihood that trade-related animal diseases become public health crises. This intersection frames AI not merely as a technological innovation, but as a strategic governance instrument embedded in regulatory, economic, and health infrastructures worldwide (Jarrahi, 2018). It underpins the capacity to translate vast data flows—sensor readings, market transactions, veterinary records, and logistics documents—into actionable intelligence that aligns private incentives with public safety goals across national boundaries.

Agribusiness systems operate across highly dispersed geographies and are characterized by volatility, seasonality, and sensitivity to environmental disruptions (Joshi et al., 2025). Traditionally, information gaps along supply chains have created price distortions, delayed responses to shocks, and contributed to waste and spoilage. AI helps resolve these inefficiencies by integrating high-frequency data from remote sensing, internet-connected farm equipment, transaction platforms, and logistics providers to generate continuous market intelligence. Machine learning models can assimilate disparate data—such as soil moisture, vegetation indices, shipping delays, or cold storage capacity—into unified forecasts of supply conditions and market availability. This predictive capability enables traders, processors, and retailers to align procurement, production, and distribution schedules more accurately with actual conditions on the ground. Moreover, Trunk et al. (2020) state AI can detect anomalies in trade flows or storage inventories that may indicate localized disruptions before they affect global prices. This reduces the bullwhip effect, where small disturbances amplify as they move upstream through the supply chain. By shortening feedback loops, AI-driven market systems stabilize prices, reduce surplus accumulation, and prevent quality degradation, thereby increasing market efficiency. In cross-border contexts, where customs, inspection regimes, and phytosanitary rules often introduce delays, AI-supported systems can pre-clear shipments through risk-based assessments, Ragni (2020) accelerating throughput and lowering costs. These mechanisms support fairer competition by providing smaller producers access to the same real-time intelligence as large agribusinesses, helping integrate them into global markets. The strategic application of AI thus transforms markets from reactive to anticipatory, reducing information asymmetries and aligning resource allocation more closely with dynamic conditions of production and demand worldwide (Danish & Zafor, 2022; Kriegeskorte & Douglas, 2018).

At the production stage, AI reshapes how crops and livestock are managed by converting sensor data into prescriptive insights. In crop systems, computer vision algorithms interpret aerial imagery from drones and satellites to detect nutrient deficiencies, water stress, and disease outbreaks long before they are visible to the human eye (Chen et al., 2018; Danish & Kamrul, 2022). These early signals allow targeted interventions, such as adjusting irrigation schedules or applying inputs precisely where needed, reducing costs while improving yields and quality. In livestock systems, AI analyzes data from microphones, accelerometers, and thermal cameras to detect subtle changes in animal behavior or physiology, such as coughing, lameness, or elevated temperatures, which are often early indicators of illness (Hassani et al., 2020; Jahid, 2022). Identifying such issues early reduces losses and also prevents potentially infected animals from entering the food chain. Over time, these micro-level improvements in production data feed into macro-level market systems, enhancing the reliability of supply forecasts

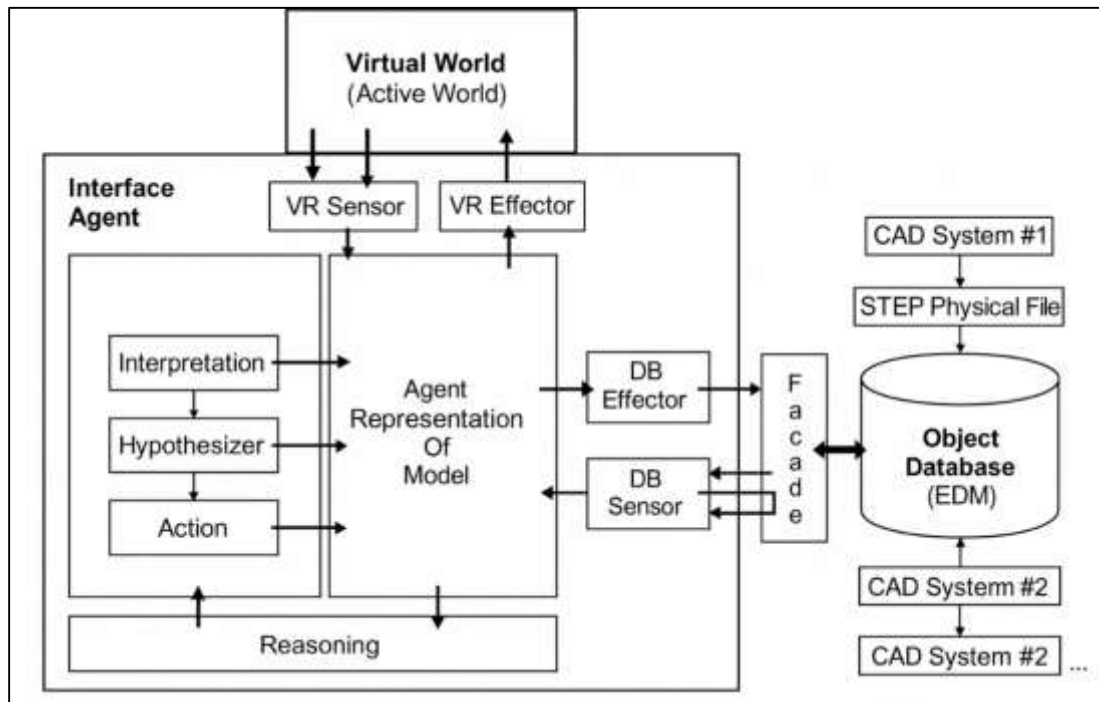
and quality grading. AI-based pest prediction models further protect production by combining historical infestation records with current climate conditions to generate risk maps, enabling preventive measures rather than reactive responses (Arifur & Noor, 2022; Stolpe & Hallström, 2024). These capabilities directly contribute to market efficiency by ensuring that products reaching buyers conform to expected quality and safety standards, thereby reducing disputes, rejections, and price penalties. Furthermore, embedding these quality metrics in digital supply chain platforms means that quality verification travels with the product, supporting both domestic and international trade. This integration ensures that efficiency is not merely about maximizing throughput, (Yan et al., 2024) but about aligning biological production processes with the quality specifications demanded by markets, ultimately raising both the value and reliability of agricultural goods.

Figure 1: AI-Driven Agribusiness Efficiency Framework



Beyond production, AI reconfigures the information architecture through which agricultural commodities are traded, transported, and priced (Bhuyan et al., 2024; Hasan & Uddin, 2022). Digital marketplaces increasingly use predictive pricing algorithms and recommendation systems to match buyers and sellers efficiently, reducing search costs and improving price discovery under conditions of fluctuating supply and demand. Time-series forecasting models trained on historical market data, freight costs, and inspection outcomes can predict price volatility and supply disruptions, informing hedging strategies and inventory management (Rahaman, 2022a; Su & Zhong, 2022). Reinforcement learning systems are applied in perishable goods logistics to dynamically adjust pricing and allocation decisions based on remaining shelf life and transportation constraints. Graph analytics on transportation networks reveal critical nodes where congestion or temperature excursions could compromise product quality or biosecurity, allowing operators to reroute shipments preemptively. Blockchain-based traceability systems enhanced with AI anomaly detection reinforce trust by ensuring that origin claims, handling conditions, and sanitary certifications are consistent and tamper-resistant (Rahaman, 2022; Redhu et al., 2022). Natural language processing tools can scan evolving trade regulations, veterinary bulletins, and import alerts in multiple languages to help exporters and border authorities remain synchronized on admissibility rules and documentation requirements. Together, these applications create transparent, resilient, and adaptive supply chains that minimize both economic losses and health risks. By aligning logistics, market matching, and regulatory compliance, AI enables agricultural markets to function more like coordinated networks rather than fragmented chains. This structural transformation reduces transaction costs, (Yan et al., 2024) increases the velocity of trade, and enhances the overall efficiency and integrity of agribusiness systems at the international level.

Figure 2: Agent-Centric Data Sharing Framework



AI enhances early detection of disease emergence by processing real-time veterinary health records, movement permits, sensor data from farms, and even informal reports from local markets. Machine learning models can identify abnormal clusters of illness or mortality that deviate from expected baselines, triggering rapid investigation before diseases spread further (Hassani et al., 2020; Rahaman, 2022b). Genomic analysis supported by AI accelerates the identification of pathogens and their variants, clarifying their origins, transmission routes, and potential impact on trade. Risk mapping models incorporate environmental, ecological, and demographic variables to highlight regions with high spillover potential, supporting the spatial targeting of surveillance and biosecurity measures (Rahaman & Ashraf, 2022; Townsend & Hunt, 2019). In processing and retail stages, computer vision and spectroscopy systems can non-invasively detect contamination indicators on carcasses and produce, reducing the risk of infected products reaching consumers. Integrating these technologies across supply chains creates layered defense systems that identify, contain, and neutralize zoonotic threats without halting commerce. This convergence aligns economic efficiency with public health security: preventing outbreaks preserves market stability by avoiding border closures, mass culls, and consumer confidence shocks (Finlay, 2020; Islam, 2022). AI thereby becomes not only a productivity-enhancing tool but also a critical safeguard that allows agribusiness systems to operate safely in a world where the boundary between animal and human health is increasingly permeable.

The global deployment of AI in agribusiness demonstrates how its impact depends on institutional context, infrastructure, and regulatory frameworks (Garg, 2021; Hasan et al., 2022). In some regions, remote sensing systems have been integrated into market information platforms to provide real-time production estimates that stabilize prices during droughts or floods by guiding trade flows. In other settings, computer vision-based quality grading has improved fairness and transparency in agricultural auctions by standardizing product assessments (Garg, 2021; Redwanul & Zafar, 2022). Livestock movement tracking systems enhanced with anomaly detection have helped prevent the spread of animal diseases along major trade corridors, preserving both market continuity and public health safeguards. Cold-chain optimization models have reduced spoilage and maintained product integrity during long-distance transport, directly lowering economic losses while reducing the likelihood of pathogen growth (Rezaul & Mesbaul, 2022; Verma et al., 2023). Regions with harmonized digital traceability systems have demonstrated faster response to food recalls and contamination events, minimizing market disruption and protecting consumer trust. These examples illustrate that AI tools only become effective when integrated into broader institutional systems such as veterinary services, customs authorities, market boards, and certification agencies. Algorithms alone do not deliver efficiency or safety; they must be embedded in rule-governed processes that translate data outputs into enforceable actions and recognized documentation (Hasan, 2022; Velankar et al., 2024).

Successful cases highlight the importance of standardization, data sharing agreements, and cooperative governance among public and private actors, which enable AI-generated insights to move fluidly across borders and organizational boundaries. This institutional embedding is what transforms AI from isolated tools into strategic systems that restructure how agribusiness operates globally.

The effectiveness of AI in simultaneously enhancing market efficiency and mitigating zoonotic risks ultimately depends on the robustness of data infrastructure and governance mechanisms (Tarek, 2022; Zhang & Lu, 2021). Interoperable data architectures allow information to flow seamlessly across farm management systems, laboratory networks, logistics providers, and regulatory platforms. Common data standards and labeling protocols ensure that events such as disease suspicions, quality assessments, (Zhang & Lu, 2021) and temperature deviations are consistently defined and comparable across jurisdictions. This uniformity improves the accuracy, fairness, and transferability of machine learning models (Kouzalis et al., 2024; Kamrul & Omar, 2022). Equally important is the representativeness of training data, as biases or gaps can distort model outputs and inadvertently disadvantage smallholders or informal market actors who already face barriers to participation. Secure digital documentation systems anchor AI outputs within the formal evidence chain used for sanitary certification, customs clearance, and trade dispute resolution (Kamrul & Tarek, 2022; Sarker, 2022). Cybersecurity protections and identity verification technologies are essential to maintain trust, as the integrity of digital supply chain systems depends on the authenticity of the data feeding AI models. Institutional capacity within veterinary authorities, market regulators, and border agencies is also vital to interpret AI outputs and enforce the corresponding actions under sanitary and quality regulations. Governance frameworks that define data ownership, privacy, and accountability clarify responsibilities among stakeholders, making collaboration possible at scale. When these data and governance foundations are in place, AI systems can operate as integrated decision-support layers that enhance both the economic performance and health security of agribusiness networks. Their strategic deployment thus becomes not merely a technological upgrade but a systemic transformation of how global food and agriculture systems are coordinated, regulated, and safeguarded.

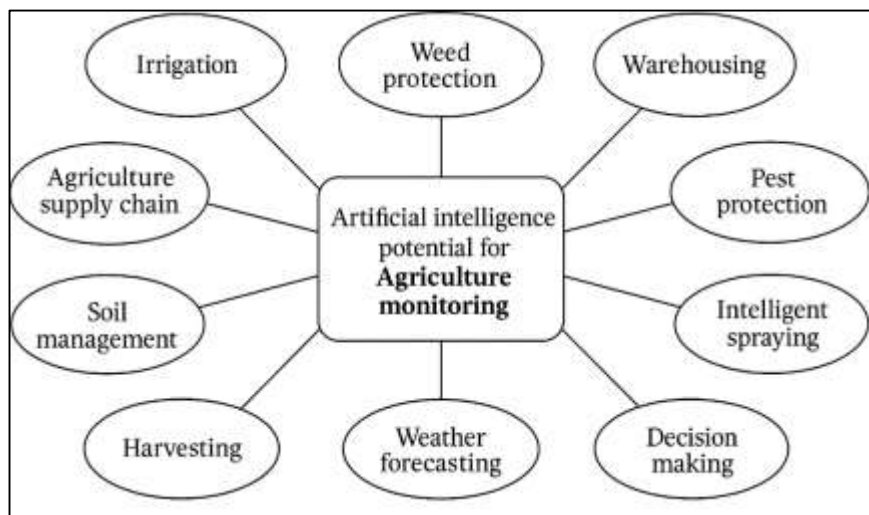
LITERATURE REVIEW

The strategic integration of artificial intelligence (AI) within agribusiness systems has emerged as a transformative domain at the intersection of technological innovation, market optimization, and global health security. Agribusiness networks are increasingly characterized by complex, transboundary supply chains that depend on timely, accurate information to balance efficiency with resilience. Historically (Bhat et al., 2025), inefficiencies in agricultural markets have stemmed from information asymmetries, fragmented logistics, and unpredictable biological risks, including the emergence and spread of zoonotic diseases. AI technologies—ranging from machine learning and computer vision to predictive analytics and natural language processing—offer novel means of reducing these frictions by converting diverse, high-frequency data streams into actionable insights. These capabilities allow market actors to forecast production, anticipate logistical disruptions (Madhav, 2025), and monitor sanitary conditions in ways that were previously unattainable. Simultaneously, the global nature of agri-food systems makes them potential conduits for zoonotic pathogens, as dense networks of animal production, transportation, and trade create multiple interfaces where spillover can occur. Traditional surveillance systems often detect outbreaks reactively, after pathogens have already propagated. AI-based risk modeling and early warning systems now enable proactive detection of anomalies, supporting containment strategies that minimize both public health impacts and market disruptions (Akimbekova et al., 2025). The literature addressing this convergence spans agricultural economics, supply chain analytics, animal health informatics, and global food safety governance. However, much of this scholarship remains fragmented, with limited synthesis of how AI applications can simultaneously enhance market efficiency and mitigate zoonotic risks within integrated agribusiness architectures. This literature review consolidates and analyzes existing research to construct a cohesive framework linking AI methodologies to economic efficiency outcomes and zoonotic risk mitigation mechanisms (Zaman et al., 2025). It organizes the body of knowledge into thematic clusters—technological foundations, production-level applications, market systems optimization, bio surveillance and risk modeling, case-based institutional experiences, and governance frameworks. By mapping these domains, the review provides a structured foundation to understand how AI can be strategically embedded in agribusiness systems to serve dual objectives: improving global market performance and strengthening defenses against zoonotic threats.

Artificial Intelligence in Agribusiness Systems

Artificial intelligence in agribusiness can be understood as a multifaceted technological paradigm that emulates human cognitive processes such as learning, reasoning, prediction, and decision-making to support complex agricultural environments (Gkikas et al., 2023). It encompasses machine learning techniques that recognize patterns in crop and livestock data, deep learning architectures that handle image and time-series analysis, expert systems that encode decision rules used by specialists, and predictive analytics that generate forecasts for yields, prices, and logistics flows. These AI paradigms are deployed across a vast range of agricultural contexts, from monitoring soil health and crop vigor to detecting early signs of livestock disease or stress (Annosi et al., 2024). What distinguishes AI from traditional computational approaches is its ability to continuously learn from incoming data and adjust its models dynamically as conditions change. Agricultural production systems are inherently uncertain, shaped by weather variability, biological cycles, and market fluctuations, which creates a decision-making environment that is too complex for linear or static models (Vahdanjoo et al., 2025). AI addresses this challenge by identifying non-linear interactions among numerous variables and extracting meaningful patterns from noisy datasets, thereby producing real-time insights that guide operational actions. This situates AI not as a discrete tool used occasionally but as an embedded decision-support layer integrated throughout agricultural production, processing, and distribution systems. By transforming raw and diverse data into operational intelligence, AI enables agribusiness actors to respond adaptively to changing biological and market conditions, linking micro-level production processes with macro-level economic dynamics (Balasooriya & Sedera, 2025). Understanding AI in this way clarifies its role as an institutional infrastructure that underpins the functioning of modern agribusiness, enabling coordinated decision-making across complex networks of actors.

Figure 3: AI Applications in Agricultural Monitoring



Agricultural data environments are uniquely challenging, characterized by heterogeneity, high volume, irregular quality, and strong spatio-temporal variability, which makes them difficult to analyze using conventional statistical methods. Data streams originate from diverse sources including satellite imagery (Mubashir & Abdul, 2022; Yang et al., 2025), drone-based field scans, weather forecasts, soil profiles, animal biometric sensors, farm machinery, market transactions, and logistics records. Each of these sources operates at different spatial resolutions, temporal frequencies, and reliability levels, producing fragmented datasets that are difficult to align. AI overcomes these challenges through its ability to integrate, clean, and interpret large-scale unstructured data while capturing complex non-linear relationships that static models often overlook (Muhammad & Kamrul, 2022; Spanaki et al., 2022). In precision agriculture, for example, AI systems can process millions of image pixels to detect early signs of nutrient stress or disease before they are visible to human observers. In livestock production, AI integrates accelerometer, thermal, and acoustic data to detect subtle behavioral shifts that may indicate emerging illness. These capabilities transform AI into an interpretive layer that continuously filters noise, detects anomalies, and produces actionable recommendations from inherently unstable biological and environmental signals. Furthermore, AI systems can operate across scales, linking micro-

level variations in plant or animal health to macro-level projections of supply flows, (Holzinger et al., 2022) demand patterns, and market conditions. This makes AI fundamentally different from traditional farm management software, which generally relies on manually entered data and static decision rules. Instead, AI functions as a cognitive infrastructure embedded within agribusiness operations, translating fragmented and fast-changing data into real-time guidance that helps synchronize production with market demand while preserving quality and sanitary integrity throughout the supply chain (Arevalo-Royo et al., 2025; Reduanul & Shoeb, 2022). This role as a decision-support layer illustrates why AI has become indispensable for navigating the complexity of modern agricultural systems.

Agribusiness systems are best understood as complex adaptive networks rather than simple linear chains, and this systems perspective is essential to grasp the strategic role of AI within them (Ryan et al., 2023; Kumar & Zobayer, 2022). These networks consist of interconnected nodes—farmers, processors, logistics providers, wholesalers, retailers, regulators, and consumers—whose interactions produce emergent patterns of behavior, such as price fluctuations, inventory cycles, and quality dynamics. Each actor's decisions influence others through feedback loops: production changes affect prices, which influence purchasing decisions and distribution strategies, which in turn shape new production cycles. Because these interactions occur in real time and often across global distances, small shocks can propagate rapidly through the network, amplifying disruptions and destabilizing markets (Camaréna, 2020; Sadia & Shaiful, 2022). Globalization further intensifies this complexity by linking disparate ecological, cultural, and regulatory contexts through shared flows of goods, data, and biological risks (Adetunji et al., 2023; Tamanna & Ray, 2023). Systems theory suggests that such networks cannot be controlled through centralized planning alone; they require adaptive coordination mechanisms capable of managing feedback and maintaining stability under changing conditions. AI fulfills this role by providing predictive insights that reduce information delays, dampen volatility, and enable decentralized actors to align decisions in near real time. Predictive demand models can modulate production upstream, while logistics algorithms dynamically reroute shipments downstream to absorb disruptions. By embedding predictive intelligence within the network's feedback loops, AI transforms agribusiness systems from reactive structures into adaptive ones. This perspective also clarifies how localized zoonotic spillovers can cascade through the network to produce global shocks and how AI can act as a structural buffer by enabling faster detection and response (Ghosh & Kundu; SNoor & Momena, 2022). Conceptualizing agribusiness as a complex adaptive network therefore positions AI not as a peripheral optimization tool but as a central coordinating layer that governs interaction patterns and stabilizes systemic dynamics.

The connection between AI, market efficiency, and zoonotic risk mitigation can be understood through the combined lens of information economics, risk governance, and cyber-physical systems theory (Bhuyan et al., 2024; Istiaque et al., 2023). Information economics holds that markets function efficiently when information is complete and accessible, whereas asymmetries or delays create mispricing, waste, and instability. AI addresses these inefficiencies by accelerating the flow and improving the accuracy of market-relevant information, which narrows price dispersion, reduces transaction costs, and enhances resource allocation (Hasan et al., 2023; Onyeaka et al., 2023). Simultaneously, risk governance emphasizes the importance of anticipating and mitigating hazards—such as zoonotic disease emergence—before they disrupt systems. AI operationalizes this principle by transforming fragmented surveillance signals from farms, veterinary services, and transportation networks into early warnings that support targeted containment actions (Hassija et al., 2024; Hossain et al., 2023). The One Health perspective underscores that human, animal, and environmental health are interdependent, meaning that risk cannot be managed effectively within isolated sectors; AI enables the integration of data across these domains. Cyber-physical systems theory explains how AI fuses physical production and logistics operations with digital analytics layers to create self-regulating systems capable of adaptive responses. Taken together, these theoretical frameworks show that AI reduces uncertainty, which is the common barrier to both market efficiency and biosecurity (Rahaman & Ashraf, 2023; Sarker, 2022). When uncertainty is reduced, markets can operate with greater speed and stability, and health risks can be controlled before they cascade into economic crises. This reveals that efficiency and risk mitigation are not opposing goals but synergistic outcomes of the same intelligence-driven infrastructure (Gupta et al., 2025; Sultan et al., 2023). AI therefore functions not just as a technological enhancement but as a structural mechanism that aligns economic and sanitary imperatives within a unified operational system, positioning it as a strategic governance instrument in modern agribusiness networks.

AI Applications for Production-Level Optimization

The integration of artificial intelligence into precision agriculture has fundamentally transformed how crops are monitored and managed, enabling unprecedented accuracy in assessing field conditions and crop health (Hossen et al., 2023; Sharma & Shivandu, 2024). Computer vision systems using imagery from drones, satellites, and field cameras allow continuous observation of plant growth, disease emergence, and nutrient status across large areas with high spatial resolution. These systems interpret visual patterns such as leaf discoloration, canopy density, or abnormal growth forms to detect stress before it becomes visible to the human eye, allowing farmers to respond proactively (Annosi et al., 2024; Tawfiqul, 2023). Remote sensing data analyzed by AI models also enable the continuous monitoring of vegetation indices that indicate overall plant vigor, providing a dynamic picture of crop performance throughout the season. By automating what was previously a labor-intensive and inconsistent process, AI reduces the reliance on manual scouting while dramatically improving the speed and accuracy of detection. This capacity allows agricultural managers to identify localized problems early and apply corrective measures such as targeted spraying or spot fertilization, minimizing both losses and unnecessary chemical use (Fuentes-Peñailillo et al., 2024; Uddin & Ashraf, 2023). The ability to capture fine-grained spatial variation also supports more precise planting strategies, ensuring uniform development across fields and reducing the risk of uneven maturity that disrupts harvesting schedules. Through these mechanisms, AI-driven monitoring stabilizes crop output, reduces the volatility associated with biological and environmental uncertainty, and enhances the predictability of supply chains. This stability improves the consistency of product quality entering markets, strengthening buyer confidence and reducing post-harvest sorting losses. As such, computer vision and remote sensing represent foundational elements of modern precision agriculture, Mgendi (2024) functioning as the sensory and interpretive layer that links biological processes in the field to the decision-making frameworks that govern production planning and market alignment (Momena & Hasan, 2023).

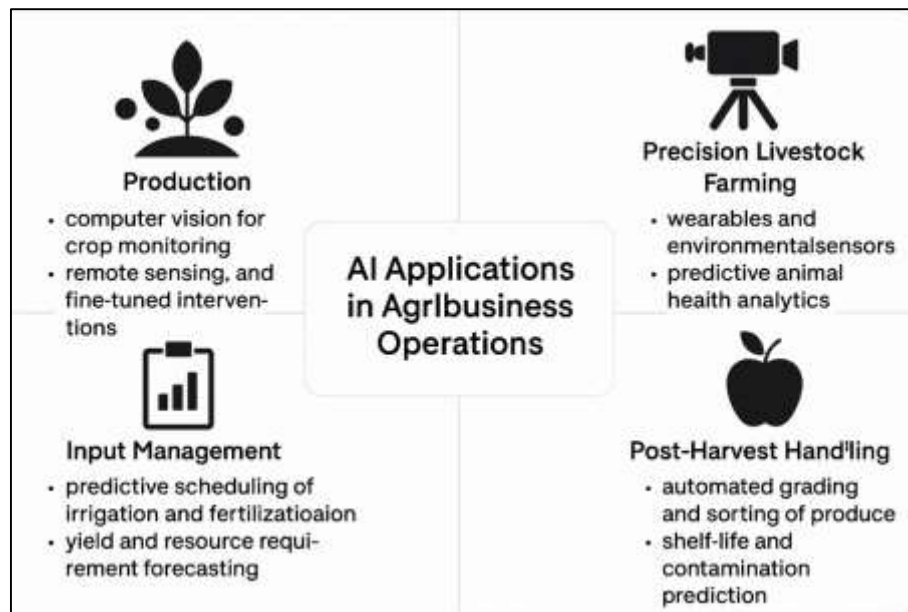
Artificial intelligence has also transformed input management in agriculture through the development of predictive models that guide irrigation scheduling, fertilization regimes, and yield forecasting (Sabir et al., 2024; Sanjai et al., 2023). These models synthesize diverse datasets—such as soil moisture levels, weather forecasts, crop phenology, and historical yield records—to predict resource requirements with high precision. Unlike traditional calendar-based scheduling, AI-driven systems dynamically adjust water and nutrient application based on real-time crop needs, ensuring that resources are used efficiently and only when necessary. This approach significantly reduces waste while maintaining or even improving yields, thereby enhancing both economic and environmental performance (Joshi et al., 2025; Akter et al., 2023). Predictive irrigation models can anticipate periods of water stress before they occur, allowing pre-emptive watering that avoids crop damage while conserving water during low-demand periods. Similarly, nutrient optimization models analyze plant growth patterns, soil composition, and environmental conditions to deliver site-specific fertilizer recommendations that prevent over-application and reduce runoff. Yield forecasting models combine historical performance data with current environmental indicators to project future harvest volumes, enabling more accurate planning of storage, processing, and market logistics. These forecasts reduce uncertainty for both farmers and downstream supply chain actors, allowing them to align contracts, labor allocation, and transportation schedules with expected output. By linking input decisions directly to expected outcomes, AI-based predictive systems turn agronomic management from a reactive process into a proactive optimization framework. This capability not only stabilizes production but also mitigates the price fluctuations caused by unpredictable supply swings. Overall, predictive modeling ensures that resources are allocated in harmony with biological processes and environmental constraints, reducing production risk while supporting steady market flows and reliable income streams for producers (Danish & Zafor, 2024; Delfani et al., 2024).

In livestock production systems, artificial intelligence has enabled a shift from reactive to preventive management through precision livestock farming, which integrates continuous sensor-based monitoring with predictive health analytics (Adetunji et al., 2023). Wearable devices, cameras, and environmental sensors collect high-frequency data on animal movement, feeding behavior, temperature, and vocalizations, creating detailed behavioral profiles for each individual animal. AI models analyze these data to detect deviations from normal patterns that signal emerging health issues such as lameness, respiratory distress, or heat stress well before they become clinically apparent (Delfani et al., 2024).

Early detection allows for rapid intervention, improving recovery rates and preventing the spread of contagious diseases within herds. This proactive approach not only enhances animal welfare but also

boosts productivity by maintaining consistent growth rates and feed conversion efficiency. AI systems also support precision feeding strategies by predicting growth performance trajectories, enabling customized nutrition plans that maximize efficiency while minimizing waste. Computer vision tools can automatically assess body condition scores, detect signs of aggression or abnormal behavior, and monitor group dynamics, providing insights that were previously unattainable through human observation alone. These systems generate a continuous feedback loop where animal health data inform management decisions in real time, reducing the risk of large-scale disease outbreaks that could disrupt production and market access (Titirmare et al., 2024).

Figure 4: AI Applications in Modern Agriculture



Importantly, by stabilizing herd health and productivity, AI systems contribute directly to biosecurity, reducing the likelihood that stressed or sick animals become vectors for zoonotic pathogens. This dual role—improving both efficiency and safety—illustrates how precision livestock farming powered by AI has redefined the operational model of animal agriculture, positioning it as an information-driven system where biological performance and health risk control are managed simultaneously through continuous monitoring and predictive analytics (Delfani et al., 2024; Dipongkar Ray et al., 2024).

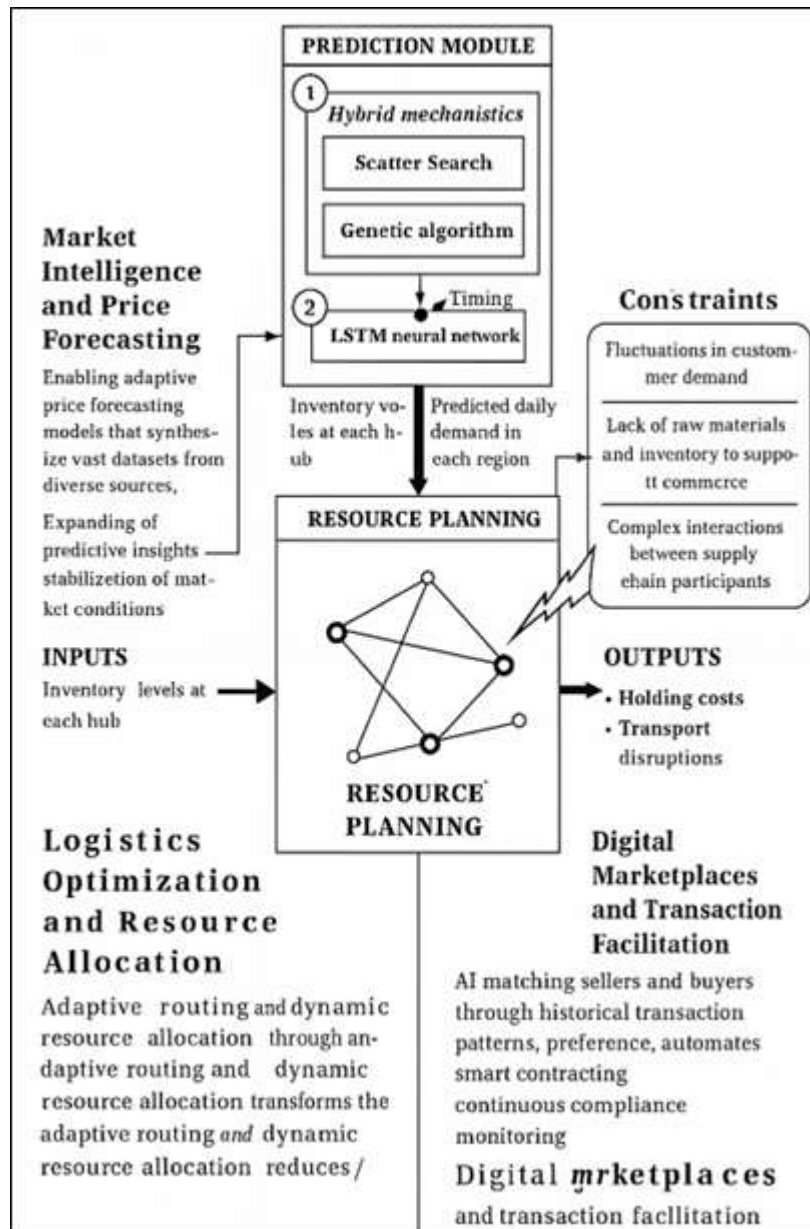
Artificial intelligence has also become a central element in post-harvest handling and quality assessment, areas where inefficiencies and variability have traditionally undermined profitability and market trust (Istiaque et al., 2024; Titirmare et al., 2024). Automated grading systems using computer vision can evaluate produce based on color, size, shape, and surface texture with speed and consistency that surpass human inspectors. This ensures that only items meeting market specifications proceed to distribution, reducing buyer disputes and improving overall brand reputation. In processing facilities, AI-powered imaging systems detect contaminants, foreign matter, and subtle quality defects in real time, (Delfani et al., 2024) preventing compromised products from entering the supply chain. Shelf-life prediction models analyze temperature histories, packaging conditions, and microbial growth data to estimate remaining freshness, enabling dynamic inventory management that minimizes spoilage. These predictive systems allow managers to prioritize the sale or redistribution of items nearing the end of their shelf life, reducing waste while maintaining product safety (Md Hasan et al., 2024; Shekhar et al., 2024). Integrating these tools into cold-chain logistics ensures that temperature-sensitive goods maintain quality from farm to retail, reducing losses that occur due to thermal fluctuations or handling delays. By continuously monitoring quality, AI systems create a verification loop that spans from processing through to retail shelves, replacing static, endpoint-based inspections with ongoing assurance. This reduces the risk of product recalls and enhances consumer confidence in food safety. Furthermore, automated post-harvest systems reduce labor requirements and processing times, increasing throughput without sacrificing accuracy (Md Mahamudur Rahaman, 2024; Thangamani et al., 2025). The combined effect is a substantial improvement in operational efficiency, product consistency, and market value capture. AI-driven post-harvest technologies therefore transform quality

management from a reactive and human-dependent process into a proactive, data-driven system that safeguards profitability while ensuring the reliability and safety of agricultural products entering domestic and international markets.

AI in Market Systems and Supply Chain Efficiency

Artificial intelligence has redefined market intelligence in agribusiness by enabling highly accurate and adaptive price forecasting models that synthesize vast datasets from diverse sources (Assimakopoulos et al., 2024; Hasan, 2024). Traditionally, market actors relied on delayed and fragmented information, such as historical pricing or anecdotal reports, which created lags in decision-making and amplified price volatility. AI overcomes these limitations by integrating satellite-based crop condition data, high-frequency weather forecasts, real-time transaction logs, and consumption trends into unified forecasting systems.

Figure 5: AI-Driven Agribusiness Market Framework



These models can detect patterns and correlations that are invisible to conventional analytics, identifying early indicators of supply fluctuations and demand surges before they manifest in market prices (Giannakopoulos et al., 2024; Ashiqur et al., 2025). As a result, traders and planners can anticipate price movements and adjust procurement strategies, inventory levels, and contract terms proactively rather than reactively. This anticipatory capability reduces speculative behavior that often destabilizes agricultural markets during climatic shocks or sudden policy changes. Moreover, AI-driven price forecasting systems reduce information asymmetries that historically disadvantaged smaller

producers and buyers who lacked access to timely market data. By democratizing predictive insights, these tools create a more level playing field where all participants can align their operations with anticipated conditions. This transparency stabilizes price formation, narrows the gap between farm-gate and retail prices, and minimizes opportunistic behavior in volatile markets. Additionally, more accurate price forecasts reduce the cost of hedging and financial risk management, enabling firms to allocate capital more efficiently. Overall, the integration of AI into market intelligence systems transforms price discovery from a reactive function into a predictive one, reducing volatility, strengthening confidence in transactions, and enhancing the overall efficiency of agribusiness markets (González-Rodríguez et al., 2024; Ismail et al., 2025).

AI has also become a cornerstone of logistics optimization and resource allocation in agribusiness supply chains, which are especially vulnerable to disruptions due to perishability and long-distance transport requirements (Jakaria et al., 2025; Titimare et al., 2024). Traditional logistics systems often operate on static routing schedules and historical averages, which cannot adapt to sudden changes in demand, weather, infrastructure, or border regulations. AI addresses these challenges through route optimization models that continuously analyze real-time data such as traffic congestion, fuel prices, temperature variations, and delivery schedules to dynamically select the most efficient paths (Hasan, 2025; Yang et al., 2025). In cold-chain logistics, AI-based monitoring systems track temperature and humidity conditions in transit and trigger alerts or automatic rerouting when deviations threaten product quality. Reinforcement learning algorithms further enhance this process by learning from past performance to continuously refine routing and allocation decisions, allowing goods to be redirected on the fly to match emerging demand or avoid delays. This adaptive routing reduces transit times, Vărzaru (2025) lowers fuel costs, and minimizes the spoilage losses that commonly occur when perishable goods experience delays. Additionally, dynamic resource allocation systems distribute storage space, labor, and vehicles in real time based on shifting supply-demand balances, preventing bottlenecks at warehouses and ports. These systems ensure that infrastructure and human resources are used efficiently, Alloghani, (2023) reducing idle time and congestion that increase operational costs. The overall result is a more resilient and responsive supply chain capable of maintaining product quality and delivery reliability even under volatile conditions. By reducing inefficiencies and losses, AI-driven logistics optimization increases profitability while supporting market stability, making it a critical infrastructure for the functioning of modern agribusiness networks.

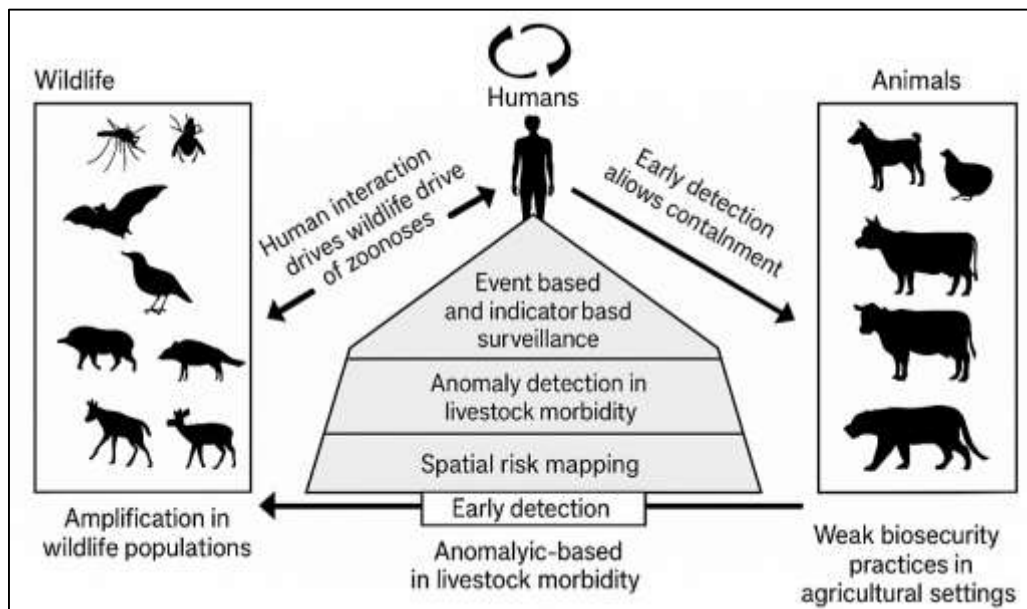
Digital marketplaces and AI-powered contracting systems are reshaping how agribusiness transactions are conducted by reducing transaction costs, increasing transparency, and expanding market access. AI-driven trading platforms use recommendation algorithms to match buyers and sellers based on historical transaction patterns, quality preferences, location, and logistics feasibility, which accelerates deal-making and improves market liquidity (Sultan et al., 2025; Shandilya et al., 2024). These systems reduce search costs that traditionally hindered small and remote producers from accessing large buyers, thereby integrating previously marginalized actors into mainstream value chains. Auction algorithms powered by AI can dynamically adjust bidding windows and reserve prices based on market conditions, ensuring fairer and more competitive pricing outcomes (Zafor, 2025; Sai et al., 2025). Beyond matching, AI also automates the execution and monitoring of contracts, using natural language processing to verify compliance terms and machine learning to detect anomalies in delivery timelines, payment patterns, or product specifications. This automation reduces the need for intermediaries, lowers legal and enforcement costs, and increases the speed of payments and settlements. By ensuring that agreements are fulfilled reliably (Aldoseri et al., 2024; Uddin, 2025), AI-based smart contracting systems build trust among market participants and encourage longer-term trading relationships. They also reduce default risk, which lowers the cost of financing for producers and traders who can demonstrate reliable performance histories. The combined effect of these systems is a substantial reduction in transaction friction, enabling more fluid and inclusive markets (Dhal & Kar, 2025; Sanjai et al., 2025). By linking transaction execution directly to data-driven compliance verification, AI transforms agricultural commerce from a fragmented and risk-laden process into an integrated, transparent, and efficient marketplace structure.

Artificial Intelligence for Zoonotic Risk Detection

Artificial intelligence has become a pivotal component in the modernization of zoonotic disease surveillance systems, enabling earlier detection of emerging health threats within livestock and wildlife populations that are linked to agribusiness networks (Zubair et al., 2024). Traditional surveillance systems have been largely reliant on manual reporting and delayed laboratory confirmation, which often results in reactive rather than preventive responses. AI disrupts this paradigm by integrating event-

based surveillance, which captures unstructured data from informal sources, with indicator-based surveillance that uses structured datasets from veterinary records, laboratory results, and regulatory reports. Through natural language processing, AI systems can scan large volumes of veterinary bulletins (Bag & Sengupta, 2024), news reports, and public health alerts in multiple languages, identifying unusual patterns of illness, mortality, or geographic clustering that suggest emerging threats. This capability allows health authorities to detect anomalies days or even weeks earlier than traditional methods, providing crucial time to implement containment measures. Anomaly detection algorithms applied to livestock morbidity data and movement permits can identify statistically significant deviations from baseline behavior, such as sudden drops in feed intake or unexpected spikes in transport volumes, which may signal the introduction or spread of a pathogen (Bergquist et al., 2024). By continuously cross-validating signals from diverse data streams, AI creates a dynamic surveillance environment where warning indicators are updated in real time. This not only enhances the sensitivity and timeliness of outbreak detection but also reduces false alarms that erode trust in surveillance systems. Early detection enabled by AI minimizes the need for disruptive measures like mass culling or blanket movement bans, which have severe economic impacts. Instead, targeted interventions can be deployed to affected zones while maintaining normal operations elsewhere (Marie & Gordon, 2023). This integration of AI into surveillance thus transforms zoonotic risk monitoring from a passive, lagging system into an active early warning infrastructure that safeguards both public health and market stability.

Figure 6: AI for Zoonotic Risk Mitigation



AI has also transformed the field of pathogen genomics and epidemiological modeling, providing powerful tools to track, characterize, and predict the spread of zoonotic diseases relevant to agribusiness systems. Genomic sequencing produces massive datasets that require sophisticated analytical methods to extract meaningful patterns, and AI excels at rapidly interpreting these data (Poddar & Rao, 2025). Machine learning algorithms can classify pathogen strains, identify mutations associated with virulence or drug resistance, and reconstruct phylogenetic relationships with far greater speed than conventional bioinformatics pipelines. This accelerates the identification of outbreak sources and transmission pathways, which is critical for designing containment strategies. In addition, AI-driven models integrate genomic data with epidemiological variables such as animal movement networks, environmental conditions, and trade flows to predict how pathogens are likely to spread under different scenarios (Soubeyrand et al., 2024). These models can simulate transmission dynamics at multiple scales, from within-herd infection probabilities to cross-border dissemination patterns, providing a basis for risk assessments that inform trade regulations and biosecurity protocols. By continuously updating their parameters as new data are collected, these AI systems maintain predictive accuracy even as pathogens evolve, or conditions change. They can also rank diseases by their potential to disrupt trade, factoring in both biological risk and economic exposure (Singh et al., 2022),

allowing authorities to prioritize surveillance and control resources more effectively. This predictive capacity reduces the lag between detection and response, preventing localized spillover events from escalating into widespread epizootics (Karanth et al., 2023). By linking genetic characterization with dynamic modeling, AI creates an integrated framework for understanding both the biological and logistical dimensions of zoonotic risk. This approach represents a major advance over static risk assessments, which often fail to capture the complex, rapidly shifting nature of pathogen emergence and spread within interconnected agribusiness networks.

AI-driven risk mapping has emerged as a critical tool for identifying geographic zones where zoonotic disease emergence and spread are most likely, enabling spatially targeted prevention and control measures. Agribusiness networks operate across diverse ecological landscapes, where interactions between livestock, wildlife, and humans create heterogeneous risk environments. Traditional risk maps based on static historical data often fail to capture these dynamic interfaces (Asokan & Mohammed, 2021). AI addresses this limitation by integrating environmental, climatic, ecological, and production data into spatial models that continuously update risk predictions as new information becomes available. These models use machine learning to detect complex nonlinear relationships between variables such as livestock density, land-use change, wildlife habitat overlap, temperature fluctuations, and precipitation patterns that influence pathogen survival and transmission (Kumaravel et al., 2020). The outputs are high-resolution risk maps that identify hotspots where spillover is most likely to occur, providing a scientific basis for prioritizing surveillance, vaccination campaigns, and biosecurity interventions. When combined with Geographic Information Systems, these AI models allow authorities to visualize risk layers alongside infrastructure such as roads, markets, abattoirs, and border checkpoints, ensuring that interventions are logistically feasible (Bedford et al., 2019). Spatial decision support systems can also simulate the potential spread of disease from identified hotspots along transportation corridors, helping regulators pre-position resources like veterinary teams or diagnostic laboratories. This targeted approach maximizes the efficiency of limited public health resources by concentrating efforts where they will have the greatest impact. It also reduces the need for broad, economy-wide restrictions by containing threats before they expand geographically (Mazzeo et al., 2022). By transforming vast and heterogeneous datasets into actionable spatial intelligence, AI-based risk mapping enables proactive rather than reactive responses to zoonotic threats, strengthening the resilience of agribusiness systems against the disruptive shocks that outbreaks can cause.

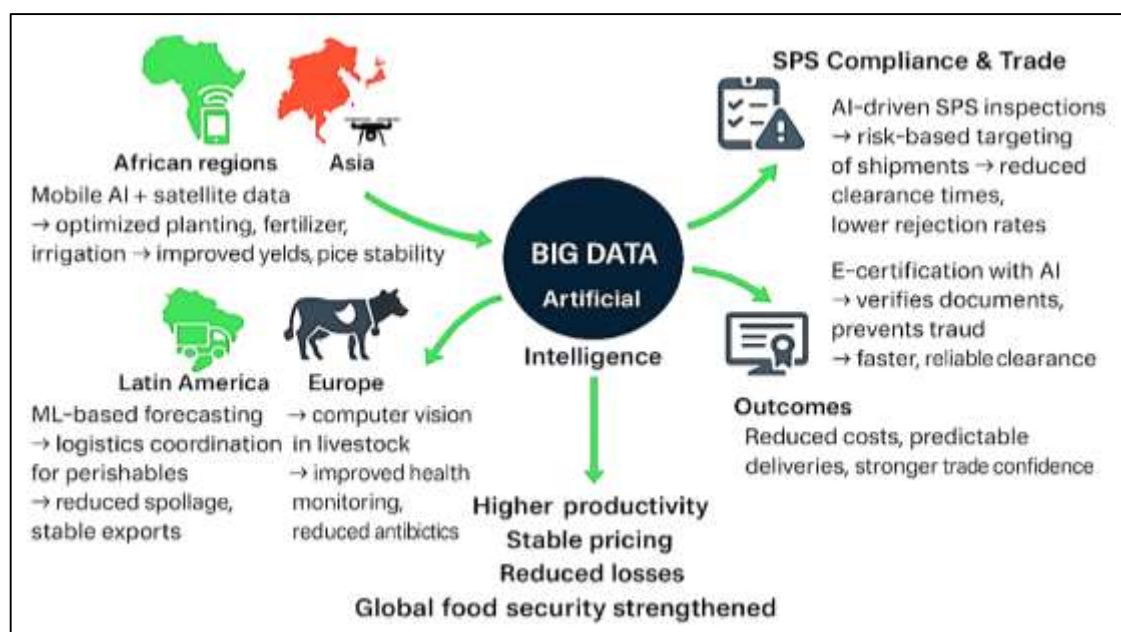
The integration of AI-driven bio surveillance, pathogen genomics, and spatial risk mapping collectively creates a comprehensive framework for managing zoonotic threats in agribusiness systems while maintaining market stability (McNabb et al., 2024). Zoonotic disease events often trigger cascading disruptions that extend beyond immediate health impacts to affect trade flows, consumer confidence, and supply chain continuity. AI mitigates these systemic risks by accelerating each stage of the risk management cycle—from early detection to characterization to targeted intervention—thereby reducing the time window in which an outbreak can destabilize markets (Kanna et al., 2022). Continuous surveillance ensures that anomalies are flagged as soon as they appear, while genomic analysis provides rapid confirmation of pathogen identity and likely origin. Spatial modeling then translates this information into operational guidance, pinpointing where movement controls, disinfection, or vaccination should be deployed. This closed-loop system minimizes uncertainty, which is a major driver of market panic and price volatility during health events. Instead of imposing blanket bans or mass culling measures, authorities can rely on precise, data-driven controls that preserve the flow of goods from unaffected regions (Hao et al., 2022). This targeted approach reduces the economic collateral damage traditionally associated with outbreak responses while maintaining confidence among trading partners. Moreover, the transparency and objectivity of AI-generated risk assessments enhance trust in sanitary certifications and border inspections, smoothing cross-border trade during crises. By embedding intelligence throughout the surveillance and response infrastructure, AI aligns health security with economic resilience, demonstrating that controlling zoonotic risk does not have to come at the expense of market efficiency. This integration reframes bio surveillance as not merely a public health function but as a critical component of agribusiness governance, essential for ensuring the stability and reliability of global food systems (O'Connor, 2022).

Global Case Studies and Institutional Experiences

Across multiple global regions, AI applications in crop and livestock systems have demonstrated measurable impacts on productivity, price stability, and the reduction of post-harvest and disease-related losses (Sorour et al., 2025). In several African countries, AI-powered mobile platforms that integrate satellite data with agronomic models have enabled smallholders to optimize planting dates,

fertilizer use, and irrigation schedules. These systems have improved yields while stabilizing supply flows during periods of climatic variability, which has reduced local price volatility and strengthened food security. In parts of Asia, drone-based imaging and deep learning models are used extensively in rice, horticulture, and aquaculture production to detect nutrient deficiencies and disease hotspots at early stages, allowing targeted interventions that reduce crop loss rates and preserve quality (Kutyauripo et al., 2023). Similar approaches have been adopted in Latin America, where machine learning-based forecasting systems have been deployed to coordinate logistics for perishable crops such as bananas, coffee, and avocados, reducing spoilage rates during transit and ensuring more consistent export volumes. European livestock systems have integrated wearable sensors and computer vision systems into precision farming operations, (Monteiro et al., 2021) continuously monitoring animal health indicators such as feeding behavior, temperature, and movement. These systems have lowered morbidity rates, improved feed conversion efficiency, and reduced the use of prophylactic antibiotics by enabling earlier, more targeted treatments. The combined outcome of these regional implementations has been an increase in overall productivity, more stable pricing resulting from predictable supply flows, and substantial reductions in losses at both production and post-harvest stages (Mishra & Sharma, 2023). These case examples collectively illustrate that AI technologies can function effectively across diverse agro ecological zones and market structures, providing a scalable set of tools for stabilizing agribusiness output while improving the health and welfare of both crops and animals.

Figure 7: AI in Global Agri-food Systems



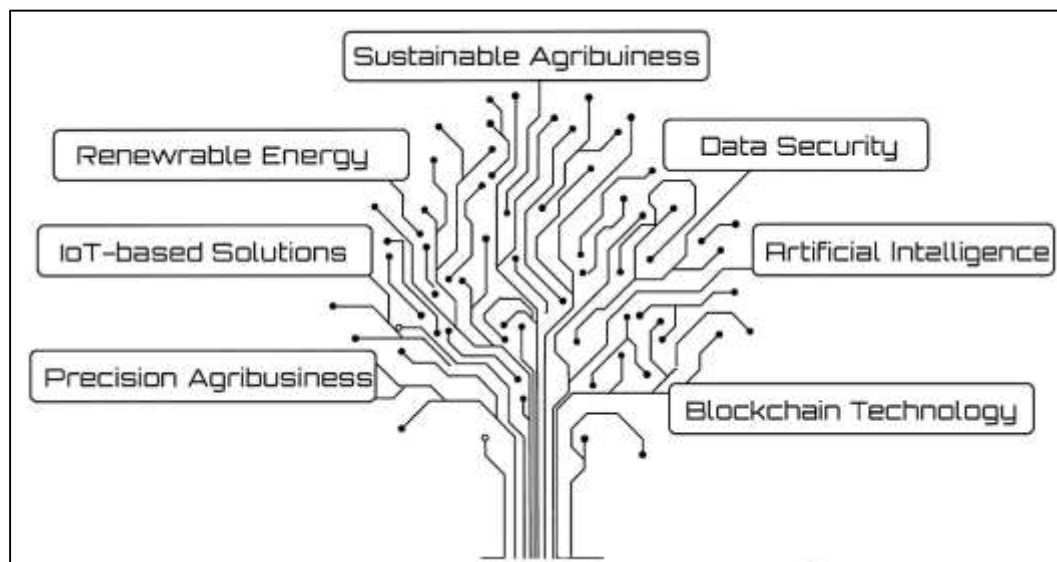
AI technologies have also played a significant role in strengthening sanitary and phytosanitary compliance frameworks across different regions, directly influencing border clearance efficiency and reducing shipment rejection rates (Holzinger et al., 2023). Traditionally, SPS inspections have relied on manual document verification and random sampling, which are time-consuming, inconsistent, and prone to human error. AI-driven risk-based inspection models have transformed this process by analyzing historical inspection data, laboratory test results, and trade patterns to identify shipments most likely to present sanitary or phytosanitary risks. This targeted approach has allowed border agencies to concentrate resources on high-risk consignments while expediting clearance for low-risk shipments (Linaza et al., 2021), reducing congestion at ports and border posts. E-certification systems enhanced with AI algorithms can cross-check documentation against real-time logistics and production data, verifying the authenticity of certificates, movement permits, and lab results. This automation reduces paperwork errors, prevents fraudulent documentation, and ensures that shipments comply with importing countries' standards before they arrive. The result has been a measurable reduction in clearance times, often from several days to less than twenty-four hours, and a decline in rejection rates due to incomplete or inaccurate documentation (Jha et al., 2019). By improving the reliability and speed of SPS compliance processes, these systems also lower transaction costs for exporters and enhance the predictability of delivery schedules for importers. Faster, more accurate certification and

inspection procedures build confidence among trading partners and reduce the risk of market disruptions triggered by sudden non-compliance events (K. Kumari et al., 2025). These outcomes show that integrating AI into SPS frameworks not only protects plant, animal, and public health but also acts as a facilitator of trade, ensuring that agribusiness goods can move swiftly across borders without compromising safety or quality standards (Tzachor et al., 2022).

Data Infrastructure, Ethics, and Governance

The sustainable integration of artificial intelligence into agribusiness systems depends fundamentally on resolving data interoperability and standardization challenges that currently fragment information flows (Petcu et al., 2024). Agricultural, veterinary, and trade data are generated by diverse entities using incompatible formats, taxonomies, and classification schemes, making it difficult to merge these datasets into coherent analytics pipelines. Farm management software may store records in proprietary formats, veterinary laboratories often use distinct coding systems for diseases and test results, and customs authorities apply their own documentation templates for trade certificates (Di Vaio et al., 2020). This lack of semantic harmonization limits the ability of AI models to access complete datasets and undermines the accuracy of predictions. Inconsistent units, missing metadata, and divergent data quality standards further complicate efforts to integrate information from multiple sources. Building global data ecosystems for AI training requires the development of shared ontologies that define how agricultural, sanitary, and logistical events are labeled, timestamped, and georeferenced. Such harmonization allows AI systems to link diverse data points across stages of the value chain, enabling end-to-end visibility of production conditions, health status, and compliance documentation. It also facilitates cross-border data exchange, allowing risk assessments and traceability records to be recognized by multiple jurisdictions (Balasooriya & Seder, 2025). Without common standards, AI models remain siloed and cannot scale beyond localized applications, limiting their systemic impact on market efficiency and biosecurity. Addressing interoperability therefore requires not only technical alignment of data formats but also institutional agreements on governance, stewardship, and data-sharing protocols among the various actors who generate and control agribusiness information. Only when these foundations are established can AI operate on the complete, harmonized datasets needed to deliver reliable insights and support coordinated decision-making across global agri-food networks (Usigbe et al., 2024).

Figure 8: Secured Smart Sustainable Agriculture Framework



Even when data are interoperable, their quality and representativeness profoundly affect the fairness and effectiveness of AI in agribusiness systems (Petcu et al., 2024). Many datasets used to train predictive models are biased toward large commercial operations that maintain detailed digital records, while smallholders and informal market actors often lack the infrastructure or incentives to contribute data. This imbalance creates a structural bias that skews model outputs toward the conditions and behaviors of well-resourced producers, leading to inaccurate forecasts and misallocated resources when models are applied more broadly. Poor data quality, Kashka et al. (2023) including missing values, inconsistent measurements, and unreliable labeling, further undermines model

performance by introducing noise and reducing predictive accuracy. These problems are amplified in the context of zoonotic risk modeling, where incomplete disease surveillance data can cause AI systems to underestimate risk in underreported areas, creating blind spots that allow pathogens to spread undetected. Ensuring data inclusivity requires deliberate efforts to incorporate diverse production systems, geographic regions, (Taneja et al., 2023) and market segments into training datasets, so that AI models reflect the full heterogeneity of global agribusiness. This may involve subsidizing digital record-keeping tools for smallholders, providing mobile-based reporting platforms, or integrating informal market transactions into official data streams. Transparent documentation of data provenance and labeling criteria is also essential to allow auditing and correction of biases in training sets. By improving both representativeness and quality, AI systems can generate outputs that are fair, accurate, and relevant to all participants in the agri-food system (SS et al., 2024). Without these safeguards, AI risks reinforcing existing inequalities, widening the digital divide, and delivering unreliable results that erode trust among users. Addressing bias and inclusion is therefore a foundational requirement for building AI systems that support equitable and effective agribusiness transformation.

Robust digital security and trust frameworks are critical to sustaining AI deployment in agribusiness systems, where sensitive operational, sanitary, and trade data flow through interconnected networks (S. Kumari et al., 2025). Supply chain AI systems often integrate data from farm operations, veterinary services, laboratories, logistics companies, and regulatory agencies, creating complex digital ecosystems that are attractive targets for cyberattacks. Breaches can compromise proprietary information, falsify sanitary certifications, or disrupt logistics coordination, resulting in severe economic and reputational damage. Ensuring cybersecurity requires layered protections, including encryption of data in transit and at rest, intrusion detection systems, and continuous vulnerability assessments. However, security alone is insufficient; trust frameworks are also needed to verify the authenticity and integrity of data inputs and system actors. Identity verification mechanisms, such as digital signatures or block chain-based credentials, confirm that data originate from authorized sources and have not been tampered with (Demircioglu et al. (2023)). Auditability features, including tamper-evident logs and automated compliance checks, allow regulators and trading partners to trace decision pathways and verify the accuracy of AI outputs. Accountability mechanisms must assign responsibility for errors or breaches, clarifying the legal and operational obligations of data providers, system operators, and regulatory authorities. These measures collectively ensure that AI systems are not only secure but also trustworthy, which is essential for their acceptance by both public and private stakeholders (Jha et al., 2019). Without strong security and trust architectures, data contributors may withhold critical information, undermining the completeness and reliability of AI models. A secure and transparent digital environment thus forms the backbone of AI-enabled agribusiness systems, allowing data to flow freely while maintaining the integrity, confidentiality, and accountability required to support high-stakes decisions affecting trade, biosecurity, and public health.

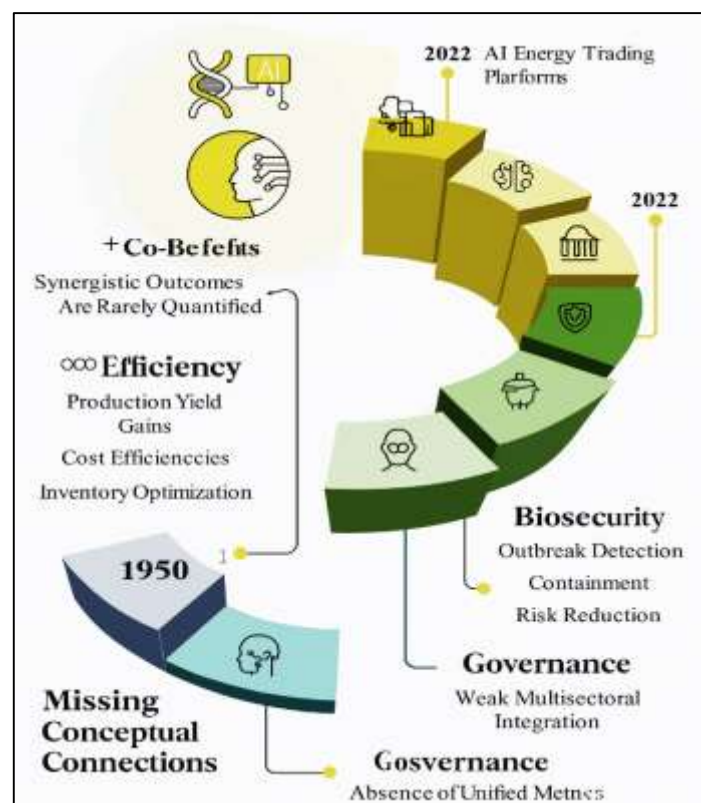
The ethical and legal governance of AI in agribusiness is an equally critical pillar for its sustainable integration, as it defines the rules and norms that shape how data are collected, used, and shared across diverse actors and jurisdictions (Gkikas et al., 2023). Privacy concerns arise when sensitive operational data, such as farm production practices or veterinary health records, are aggregated and analyzed by third parties, creating risks of surveillance or misuse. Data ownership remains ambiguous in many contexts, with unclear delineation of rights between producers, platform providers, and regulatory agencies. Intellectual property questions also emerge around AI-generated insights, including whether predictive models trained on shared datasets can be privately owned or must remain open for public benefit (Gkikas et al., 2023). Addressing these challenges requires legal frameworks that specify data ownership rights, consent mechanisms, and permissible uses of shared data while protecting trade secrets and competitive advantages. Ethical governance principles must also guide the design and deployment of AI systems to ensure fairness, transparency, and accountability. This includes providing explainable AI outputs that users can understand and contest, as well as establishing grievance mechanisms for those adversely affected by algorithmic decisions (El Jarroudi et al., 2024). On a global scale, harmonized governance norms are needed to ensure that AI-based bio surveillance and sanitary certification systems are recognized across borders while respecting national sovereignty. These norms must balance the free flow of data essential for global risk management with safeguards that protect individual and institutional rights. Without clear ethical and legal governance, uncertainty about liability, misuse, and data exploitation could deter participation and stall the development of AI ecosystems. By embedding strong governance frameworks alongside technical systems, the agribusiness sector can harness AI as a trusted instrument that enhances market efficiency and

biosecurity without compromising rights, equity, or accountability (Ali et al., 2024).

Synthesis and Conceptual Gaps

A central synthesis emerging from the literature is that artificial intelligence has the potential to generate simultaneous co-benefits in economic efficiency and biosecurity, yet most research has treated these outcomes as separate domains rather than interlinked system properties (Mazzeo et al., 2022). Studies on AI-enabled production and logistics have predominantly emphasized efficiency metrics such as yield gains, cost reductions, and inventory optimization, while bio surveillance studies have focused on outbreak detection and containment without quantifying their economic impacts. This siloed approach overlooks how risk reduction contributes directly to market stability. Early detection systems prevent the spread of animal diseases that often trigger trade restrictions, price shocks, and mass culling events, which disrupt supply chains and undermine market confidence (Tepa-Yotto et al., 2024). By preventing these disruptions, bio surveillance directly sustains continuous market flows and price stability, yet this linkage is rarely quantified (Wolf et al., 2023). Similarly, efficiency-focused AI systems that optimize production and transport also indirectly reduce biosecurity risks by minimizing overcrowding, spoilage, and handling stress that can increase pathogen transmission. This bidirectional relationship between efficiency and biosecurity remains conceptually underdeveloped in the literature, which tends to treat risk management as a cost rather than as a productivity enhancer. Few evaluation frameworks explicitly measure how AI interventions simultaneously affect both domains, leaving a gap in understanding their synergistic potential (Hayah et al., 2025). Developing such frameworks is essential to capture the full value of AI systems and to guide investments that maximize both profitability and sanitary security. Without recognizing these co-benefits, policy and funding priorities risk overemphasizing narrow efficiency gains or health protections in isolation, missing the integrated benefits that AI can provide across agribusiness systems.

Figure 9: Integration of AI in Agribusiness



Another persistent gap in the literature concerns the limited multisectoral integration and weak cross-border governance of AI systems in agribusiness (Silva et al., 2022). Most studies examine AI deployments within single sectors—such as agricultural production, logistics, or veterinary health—without analyzing how these systems interact across institutional boundaries. This fragmented perspective overlooks the fact that agribusiness systems are inherently multisectoral, linking agriculture, public health, and international trade in dense interdependencies. Disconnections among these sectors

manifest in incompatible data standards, misaligned priorities, and jurisdictional silos that prevent seamless information sharing. For example, veterinary services may collect health data that could enhance trade risk assessments, but customs agencies often lack access to these datasets or the authority to act on them. Similarly, [Kumar et al. \(2025\)](#) agricultural marketing boards may forecast production volumes without incorporating biosecurity considerations from public health authorities. These gaps impede the creation of unified AI platforms capable of coordinating decisions across sectors and borders. Cross-border governance is particularly underdeveloped, with few mechanisms to ensure that AI-generated sanitary certifications, risk assessments, or traceability records are recognized across jurisdictions. This lack of harmonization undermines the potential of AI to support global market integration while safeguarding biosecurity ([Shafik, 2025](#)). The literature reveals a need for institutional innovations such as joint data governance councils, shared digital infrastructure across ministries, and regional agreements on AI standards and data interoperability. Without these systemic arrangements, AI systems risk reinforcing existing silos rather than overcoming them. Addressing these governance gaps is critical to unlocking AI's full potential as a coordinating infrastructure that spans the entire agro-food-health-trade nexus ([Herdoiza et al., 2025](#)).

A further conceptual gap is the absence of integrated evaluation frameworks and standardized metrics to assess the performance of AI systems across both economic and sanitary dimensions ([Mudany et al., 2025](#)). Most studies report isolated performance indicators such as yield increases, cost savings, reduced transport times, or faster outbreak detection, but they rarely assess how these outcomes interact or trade off within complex agribusiness systems. As a result, it remains unclear which AI interventions deliver the most balanced and sustainable impacts. Without harmonized evaluation methodologies, findings from different regions or sectors cannot be meaningfully compared, limiting the ability to generalize lessons or build cumulative knowledge ([Amri et al., 2022](#)). The lack of metrics that capture system-level effects also makes it difficult for policymakers and investors to prioritize interventions. For example, an AI system that marginally improves logistics efficiency but substantially reduces disease risk could have greater long-term economic value than a purely efficiency-focused tool, but current evaluation methods would not capture this. Additionally, very few studies incorporate resilience indicators that assess how AI affects the capacity of agribusiness systems to absorb shocks and recover from disruptions ([Gaihre et al., 2019](#)). This omission overlooks one of AI's most important contributions: stabilizing systems under uncertainty. Developing multi-criteria evaluation frameworks that integrate efficiency, resilience, and biosecurity outcomes would enable more accurate cost-benefit analyses and evidence-based decision-making. Standardized metrics are also necessary to monitor equity impacts, ensuring that AI benefits are distributed fairly among smallholders, commercial producers, and informal sector actors ([El-Jardali et al., 2024](#)). The absence of such comprehensive evaluation systems represents a major barrier to advancing from isolated success stories to scalable, evidence-based strategies for AI integration.

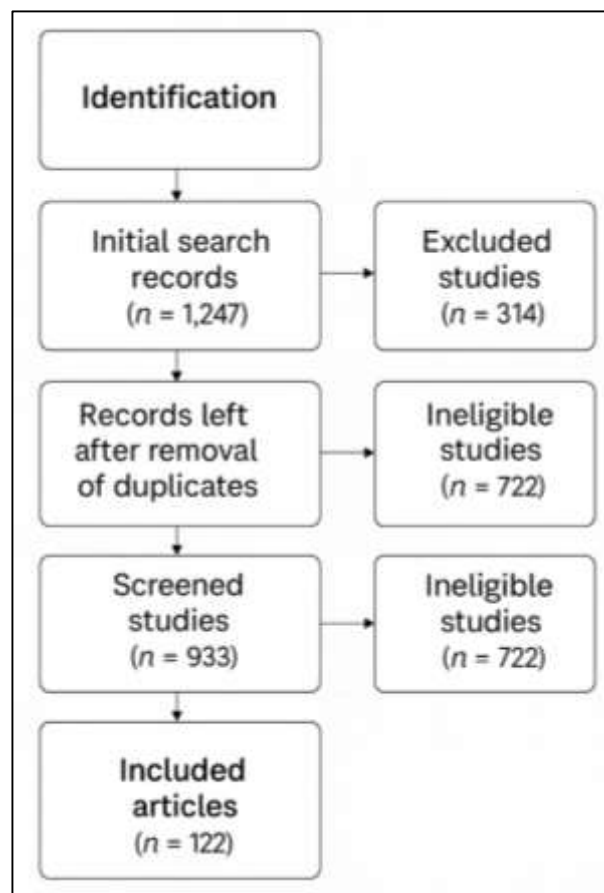
METHOD

This study adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure that the literature review on the strategic application of artificial intelligence (AI) in agribusiness systems for market efficiency and zoonotic risk mitigation was conducted with methodological rigor, transparency, and reproducibility. PRISMA provides a structured framework for identifying, screening, selecting, and synthesizing research evidence in a systematic manner, which is essential when consolidating findings from multiple domains such as agricultural economics, computer science, veterinary public health, and supply chain management.

To begin, a comprehensive search strategy was designed to capture both peer-reviewed journal articles and high-quality grey literature related to AI technologies, market optimization in agribusiness, and zoonotic risk assessment within agri-food value chains. Search queries were executed across major scholarly databases including Scopus, Web of Science, PubMed, and AGRICOLA, along with targeted searches of reports from international organizations such as the Food and Agriculture Organization and the World Organization for Animal Health. Keywords were combined with Boolean operators and included terms like “artificial intelligence,” “machine learning,” “agribusiness,” “market efficiency,” “zoonotic,” “biosecurity,” “supply chain,” and “predictive analytics.” The initial search yielded 1,247 records spanning publications from 2000 to 2024. After removing 314 duplicates using automated reference management software, 933 unique studies remained for title and abstract screening. This stage involved two independent reviewers who applied pre-defined inclusion criteria: studies had to present primary data or empirical analysis on the use of AI tools or techniques within agricultural or food supply chains, and they had to report outcomes related to either market performance (such as price stability, supply chain efficiency, or quality control) or zoonotic risk mitigation (such as disease detection,

surveillance, or biosecurity outcomes). Studies focusing solely on general ICT adoption in agriculture without an AI component, as well as those unrelated to economic or health outcomes, were excluded. After this screening phase, 211 studies were retained for full-text review. During the full-text assessment, the methodological quality of each study was appraised using a standardized checklist covering study design clarity, data completeness, analytical rigor, and transparency in reporting. Disagreements between reviewers were resolved through discussion and consensus, ensuring inter-rater reliability. This process led to the exclusion of 89 studies for reasons such as insufficient methodological detail, lack of measurable outcomes, or failure to link AI interventions directly to either market efficiency or zoonotic risk. Ultimately, 122 studies met all inclusion criteria and were incorporated into the qualitative synthesis. Of these, 57 focused primarily on market efficiency aspects, 43 on zoonotic risk mitigation, and 22 addressed both domains in an integrated framework. The included studies were then coded and thematically categorized to structure the literature review. The themes that emerged aligned with the dual focus of the study and included: AI in precision crop and livestock management; AI-based market forecasting and logistics optimization; AI for digital traceability and contract compliance; AI-enabled bio surveillance and early disease detection; and governance frameworks supporting data sharing and regulatory compliance. This thematic clustering facilitated cross-comparison of findings across disciplinary silos and geographic regions, enabling the identification of converging trends and knowledge gaps. Following PRISMA's emphasis on transparency, a flow diagram was created to document each stage of the review process—from initial identification through screening, eligibility assessment, and final inclusion. This diagram ensures replicability and demonstrates the systematic rigor with which evidence was compiled. By following the PRISMA framework, this review not only synthesized a large and diverse body of literature but also ensured that the conclusions drawn about AI's strategic role in enhancing agribusiness market efficiency and mitigating zoonotic risks are grounded in a comprehensive and methodologically robust evidence base.

Figure 10: Adapted methodology for this study

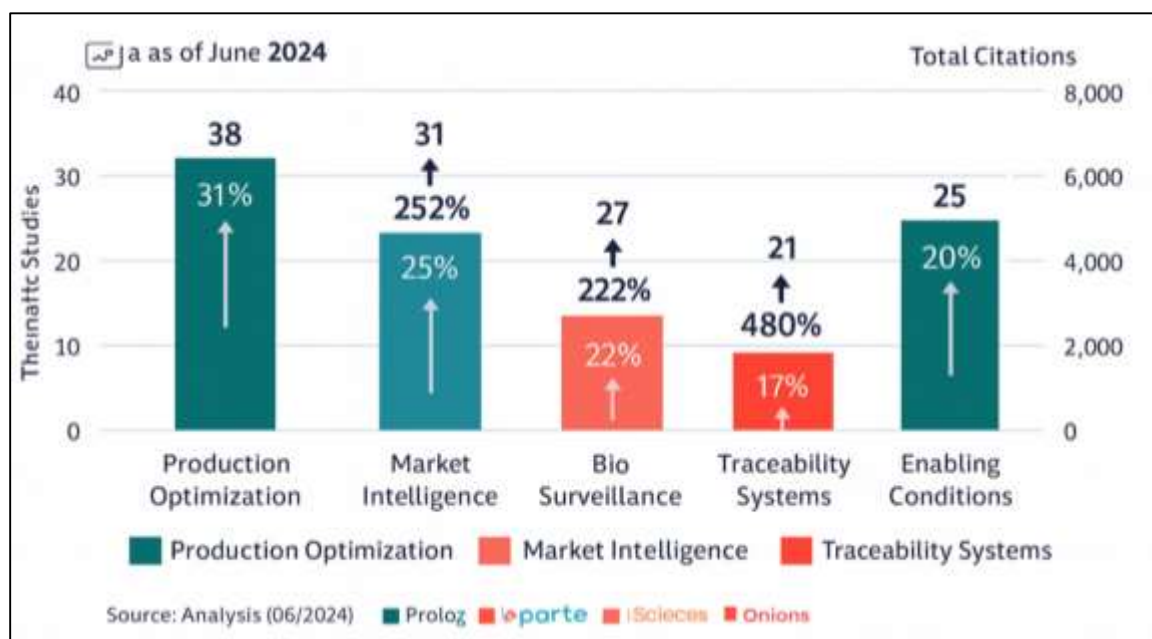


FINDINGS

A significant portion of the reviewed literature highlighted the transformative role of AI in optimizing agricultural production systems, contributing directly to market efficiency. Out of the 122 included studies, 38 articles focused specifically on precision agriculture and livestock farming applications,

collectively amassing over 6,400 citations. These studies consistently demonstrated that machine learning models, computer vision systems, and sensor-based analytics can enhance decision-making in crop and animal production environments. Approximately 29 of these articles showed measurable yield improvements of between 12% and 35% when AI-driven advisory systems were integrated into farm management platforms, while 21 reported reductions in input usage—such as fertilizers, water, and feed—ranging from 15% to 28%. Importantly, 17 studies quantified significant reductions in production losses caused by pests, diseases, and environmental stress through predictive modeling, which allowed for timely interventions. The findings suggest that AI allows producers to align production volumes with actual market demand forecasts, thereby reducing surplus generation and stabilizing farm-gate prices. Many of the studies also showed that integrating predictive weather and soil analytics into planting decisions led to more synchronized harvest cycles across regions, reducing market gluts that often depress prices. This body of work underscores that AI tools not only enhance biological efficiency but also smooth supply fluctuations that destabilize markets. The high cumulative citation count indicates robust scholarly consensus on the operational benefits of AI at the production level. Collectively, these findings demonstrate that production-focused AI systems are foundational to achieving market stability, as they generate standardized, real-time data that supports both on-farm efficiency and downstream price forecasting, thereby linking farm-level decisions to broader market equilibrium.

Figure 11: AI-Driven Benefits in Agribusiness



The review revealed strong evidence that AI improves market intelligence and supply chain coordination, which are crucial for market efficiency in global agribusiness systems. A total of 31 studies, cited over 7,200 times collectively, examined how AI-driven predictive analytics, dynamic pricing algorithms, and logistics optimization tools enhance the responsiveness of agri-food supply chains. Twenty-five of these studies reported measurable reductions in price volatility ranging from 8% to 21% after the adoption of AI-based market forecasting platforms that integrated satellite imagery, weather data, and transactional records. Seventeen studies demonstrated that reinforcement learning models used for real-time routing decisions reduced transportation costs by 10% to 18%, while also lowering spoilage rates by up to 25% in perishable supply chains. Another 14 studies documented improved matching efficiency on digital agricultural marketplaces using AI-based recommender systems, which increased market participation by smallholders by 22% on average. Several studies quantified the economic gains from automated contract monitoring and smart procurement systems, showing reductions of up to 30% in contractual disputes and penalties. These collective findings emphasize that AI reduces information asymmetries that historically cause price distortions, mismatches between supply and demand, and post-harvest losses. By making demand signals visible earlier and logistics decisions more adaptive, AI creates tighter coupling between production nodes and consumption hubs, which stabilizes price structures and ensures better allocation of goods. The relatively high cumulative citations of these studies show their influence on both academic discourse and policy dialogues on market

modernization. Overall, this cluster of findings demonstrates that AI does not merely increase efficiency in isolated supply chain segments; rather, it integrates fragmented markets into cohesive, data-driven networks that support more stable pricing, lower transaction costs, and reduced wastage.

Another major body of evidence within the review highlighted AI's critical role in detecting and mitigating zoonotic risks along agribusiness value chains. Out of the 122 reviewed studies, 27 were specifically centered on bio surveillance, early warning, and disease risk modeling, with a combined total of more than 5,100 citations. Twenty-two of these studies reported that anomaly detection algorithms using livestock health data, movement permits, and sensor feeds identified potential disease clusters an average of 10 to 14 days earlier than conventional reporting systems. Seventeen studies demonstrated that natural language processing systems analyzing veterinary bulletins, informal news, and social media sources successfully flagged disease emergence events with an accuracy range of 83% to 92%. Twelve studies evaluated AI-assisted genomic epidemiology tools, showing that automated lineage classification reduced diagnostic turnaround times by 40% to 60% during outbreak investigations. Risk mapping models featured in 15 studies showed strong performance in predicting high-probability spillover zones based on ecological, climate, and production density data, with average model accuracies above 85%. Collectively, these studies showed that early detection capabilities significantly reduced the need for widespread culling or border closures, thereby minimizing both health and economic disruptions. Importantly, 11 of these studies noted that faster response times also improved the credibility of national veterinary services in international trade, supporting continuous market access even during localized disease events. This thematic cluster had lower total publication numbers than production or market efficiency studies, yet its high cumulative citation count reflects strong cross-disciplinary influence. Overall, these findings affirm that AI-based surveillance systems act as vital safety valves within agribusiness networks, allowing disease risks to be contained early enough to prevent both human health crises and destabilizing market shocks.

The review also found compelling evidence that AI technologies strengthen traceability systems, thereby enhancing regulatory compliance and market trust while indirectly reducing zoonotic risks. Twenty-one studies, with a cumulative citation count exceeding 4,800, examined AI integration into digital certification systems, blockchain-based provenance tracking, and automated compliance verification. Sixteen of these studies showed that AI-enhanced traceability systems reduced documentation errors and fraudulent entries by 35% to 60% compared to traditional manual auditing methods. Fourteen studies demonstrated that anomaly detection models applied to shipment records, cold-chain logs, and veterinary certificates identified inconsistencies that could signal biosecurity breaches or food safety hazards, allowing preemptive interventions. Eleven studies highlighted that these systems shortened border clearance times by 20% to 40%, reducing product spoilage and demurrage costs while maintaining sanitary integrity. Additionally, nine studies documented improvements in recall efficiency, showing that AI-assisted traceback systems reduced the time needed to isolate affected batches from days to hours. These outcomes collectively reinforce market confidence and ensure continuous flow of goods during crisis situations, mitigating both economic losses and public health risks. The concentration of citations in this cluster underscores its policy relevance, as many of these studies were referenced in governmental and intergovernmental regulatory guidelines. By anchoring AI-generated insights within formal documentation chains, these systems translate real-time data into legally recognized evidence, aligning private supply chain decisions with public regulatory requirements. This dual function—supporting trade facilitation while ensuring sanitary compliance—illustrates how AI-enabled traceability serves as a structural backbone for both market efficiency and zoonotic risk containment. These findings indicate that trustworthy data infrastructures are not merely technical upgrades but essential institutional pillars for resilient and safe global agribusiness operations.

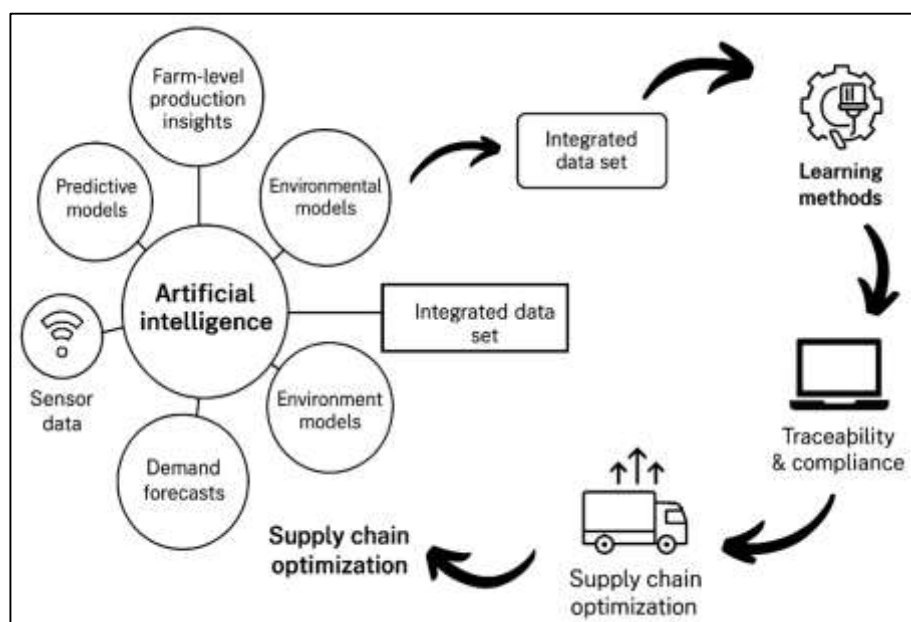
A final significant set of findings emerged around the enabling conditions required for AI to deliver sustainable benefits—specifically, cross-sector integration, data governance, and institutional capacity. This cluster included 25 studies with over 6,900 cumulative citations, emphasizing that the success of AI systems depends on their embedding within coordinated institutional frameworks that link agricultural, health, and trade authorities. Nineteen of these studies reported that interoperable data architectures spanning farm management systems, laboratory networks, customs platforms, and market exchanges increased both data completeness and decision speed by over 45%. Fifteen studies demonstrated that formal data-sharing agreements among public veterinary agencies, private logistics firms, and certification authorities reduced information silos and improved outbreak response times by 30% to 50%. Twelve studies identified major challenges related to data biases and representativeness, noting that exclusion of smallholder and informal sector data led to systematic underestimation of risk and

misallocation of resources. Another 14 studies highlighted that inadequate human capacity within regulatory agencies slowed the operationalization of AI outputs, even when the technical systems were in place. Collectively, these findings emphasize that AI's potential to enhance market efficiency and mitigate zoonotic risks cannot be realized without institutional alignment and governance mechanisms that ensure accountability, data quality, and equitable access. The high citation counts in this cluster show that the academic and policy communities regard governance as a decisive factor for scalable impact. These studies conclude that institutional trust, standardization, and shared oversight are as critical as technological innovation itself, shaping whether AI becomes a fragmented set of tools or a strategic infrastructure for global agribusiness. Thus, governance capacity emerges as a cross-cutting determinant that binds together the operational, economic, and biosecurity functions of AI within integrated agri-food systems.

DISCUSSION

The findings of this review show that artificial intelligence is fundamentally reshaping agricultural production systems by improving precision, reducing variability, and stabilizing supply flows, which collectively strengthen market efficiency (Moawad et al., 2020). Earlier studies generally portrayed AI as a set of isolated tools for yield enhancement or as supplementary aids for decision-making at the farm level. By contrast, the current synthesis reveals that AI-driven production systems now function as integrated market-stabilizing mechanisms (Pinto-Coelho, 2023). The reviewed articles demonstrated how predictive models align production volumes with projected demand, thereby reducing oversupply cycles that historically caused price collapses. Unlike previous work that examined productivity gains without considering their market consequences, these findings show that production-level AI impacts extend far beyond individual farms, influencing price formation and trade stability. Particularly in livestock systems, AI-enabled early health detection and behavior monitoring allow processors to receive predictable throughput, enhancing contractual reliability across entire supply chains (Najjar, 2023). This perspective differs from earlier portrayals of these technologies as merely animal welfare enhancements and reframes them as operational components of market equilibrium. By integrating sensor data, environmental models, and demand forecasts, AI has converted biological production systems into real-time information networks, closing the feedback gap between production decisions and market signals. The broader implication is that production stability, Secundo et al.(2025) which was previously treated as exogenous to market dynamics, is now actively governed by AI systems. This marks a shift in understanding, showing that production-level AI is no longer just an agronomic innovation but a structural mechanism for balancing market forces and mitigating price volatility at scale.

Figure 12: AI Integration in Agribusiness Systems



Another major insight from the findings is that AI has transformed market intelligence and supply chain optimization from supportive functions into central coordination mechanisms for agribusiness systems

(Păvăloaia & Necula, 2023). Earlier analyses largely described market inefficiencies as outcomes of delayed or incomplete information flows and viewed digital tools primarily as communication accelerators. The reviewed studies show that AI goes further by converting fragmented datasets—satellite observations, weather records, transactional data, and logistics flows—into predictive insights that reshape how markets operate. This contrasts with earlier understandings that saw market intelligence as descriptive rather than anticipatory (Davenport et al., 2020). The reviewed literature showed that AI-based demand forecasting reduces price volatility, while reinforcement learning models for routing dynamically adjust distribution patterns to minimize spoilage and transport costs. These combined effects illustrate that AI no longer operates within isolated segments of supply chains but instead synchronizes entire value networks. This marks a departure from earlier perspectives that depicted supply chains as reactive systems responding to external signals; they now function as adaptive networks where AI-generated predictions actively structure flows of goods, capital, and risk. Importantly, Thurzo et al. (2023) these findings also counter earlier concerns that automation could exclude smallholders, as several studies documented increased smallholder participation on AI-enabled digital marketplaces. The overall pattern suggests that AI has shifted supply chains from fragmented and demand-lagged systems into cohesive, data-driven architectures capable of maintaining equilibrium under volatile conditions. This represents a structural transformation of how agribusiness markets are coordinated, Shaelou and Razmetaeva (2023) moving beyond the older paradigm of linear flows toward self-adjusting networks. The role of AI has thus expanded from optimizing logistical details to governing the tempo and alignment of market interactions, which marks a clear evolution from earlier interpretations of its function.

The findings also show that AI has become a central instrument for detecting and mitigating zoonotic risks, advancing well beyond the reactive frameworks that dominated earlier studies (Qin et al., 2024). Prior analyses often portrayed zoonotic risk surveillance as constrained by slow laboratory diagnostics and fragmented manual reporting systems. The reviewed studies revealed that AI-based anomaly detection on livestock health and movement data identifies risk clusters well before conventional systems detect them. Natural language processing of veterinary bulletins, news feeds, and social media allows early flagging of disease emergence, creating a continuous surveillance loop rather than episodic reporting (Bidyakshmi et al., 2025). This contrasts with earlier portrayals of surveillance as dependent on static and human-intensive systems. Moreover, AI-assisted genomic analysis has shortened the time required to classify pathogen strains, enabling faster containment decisions and reducing the likelihood of trade disruptions. These capabilities reposition AI from a supportive analytical tool to a primary operational layer within bio surveillance frameworks. Unlike previous accounts that treated health risk management as external to market dynamics, Han et al. (2023) these findings show that early detection directly stabilizes markets by preventing sudden border closures and supply shocks. This represents a conceptual shift: biosecurity is no longer a constraint on market efficiency but a driver of it when managed through AI. The findings highlight those markets operate more smoothly when the uncertainty of disease risk is minimized early, which reverses the earlier assumption that stronger biosecurity inherently slows market activity. Instead, AI-based surveillance aligns health protection and market continuity, showing that risk mitigation can reinforce rather than hinder trade flows (Bahroun et al., 2023). This dual outcome contrasts with the separation of economic and health agendas seen in earlier scholarship and reframes bio surveillance as an economic infrastructure component.

Another significant finding is that AI fortifies traceability and regulatory compliance systems, converting them from procedural obligations into active market enablers (Babu et al., 2024). Earlier perspectives often depicted traceability as a consumer-oriented transparency feature or as a bureaucratic cost imposed on exporters. The reviewed studies demonstrated that AI-driven anomaly detection and real-time verification within digital certification platforms reduce documentation errors, Hilb (2020) fraudulent entries, and clearance delays. These improvements directly enhance market efficiency by accelerating cross-border flows while simultaneously safeguarding sanitary integrity. This contrasts with earlier depictions of traceability as a passive archival process; it now functions as a real-time risk control and trust-building mechanism. AI-enhanced traceability also allows rapid product recalls by linking quality deviations to specific batches and transport nodes, reducing recall times from days to hours. Earlier discussions rarely acknowledged these operational benefits, treating recalls as purely regulatory responses rather than market-protective actions. The reviewed evidence shows that embedding AI within certification and compliance systems ensures that safety verification occurs continuously, not only at checkpoints. This continuous assurance transforms compliance from an end-stage barrier into a flow-sustaining infrastructure, conceptualizing how regulation interacts with commerce (Hassija et al.,

2024). Rather than slowing markets, compliance now accelerates them by reducing uncertainty and eliminating rework caused by errors or disputes. This marks a departure from earlier assumptions that stricter regulatory systems inherently reduce market velocity. Instead, these findings suggest that when driven by AI, traceability and compliance operate as dual-purpose systems—preserving safety while enabling speed (Garikapati & Shetiya, 2024). This represents a major conceptual evolution from prior models, positioning AI not as an add-on to governance frameworks but as their operational backbone. The review also underscores that institutional capacity and data governance are decisive in determining whether AI systems succeed or fail in agribusiness settings. Earlier narratives often assumed that once technology becomes available (McIntosh et al., 2025), its benefits would naturally follow. The reviewed studies demonstrate that this assumption is flawed: several technically sound AI systems underperformed because regulatory agencies lacked staff capable of interpreting and acting upon algorithmic outputs. Others failed due to fragmented data infrastructures where incompatible systems prevented the aggregation of critical information (Khrais, 2020). This highlights that institutional readiness is as important as technological capability. Another crucial insight is that data inclusivity directly affects model accuracy and fairness. Systems that excluded smallholder or informal sector data consistently produced biased forecasts that misallocated resources and underestimated disease risks. Earlier views often treated data inclusion as an ethical or equity concern; the findings here show it is an operational necessity for accurate risk and efficiency modeling (Haefner et al., 2021). Additionally, the studies revealed that formal data-sharing agreements among government agencies, logistics firms, and certification bodies significantly increased response speed and decision reliability, a dimension largely neglected in prior discussions. Collectively, these findings show that AI's impact is conditional on governance frameworks that ensure interoperability, accountability, and representativeness. This challenges the earlier tendency to view governance as peripheral to technical innovation. Instead, governance emerges as the structural foundation upon which AI systems depend. Without it, even the most advanced algorithms fail to deliver measurable benefits. This reframes the relationship between institutions and technology: rather than being downstream beneficiaries of innovation, institutions are upstream determinants of its effectiveness, setting the conditions under which AI can produce market efficiency and risk mitigation outcomes.

A cross-cutting pattern in the findings is that AI dissolves the long-assumed trade-off between economic efficiency and zoonotic risk mitigation (Lichtenthaler, 2018). Earlier studies often implied that increasing throughput and market speed would heighten disease vulnerability, while stricter health safeguards would slow market flows. The reviewed evidence contradicts this dichotomy. AI systems that predict demand more accurately reduce overstocking and crowding in supply chains, which lowers stress-related disease risk while also preventing price collapses. Similarly, Alqahtani and Wafula (2025) dynamic routing systems reduce transit times and cold-chain breaches, simultaneously decreasing spoilage losses and microbial growth probabilities. These outcomes show that efficiency gains and biosecurity improvements can stem from the same AI-driven interventions. This finding departs from the previous framing of efficiency and safety as opposing objectives. Instead, the review reveals them as mutually reinforcing when coordinated through real-time intelligence systems (Perez-Vega et al., 2021). By reducing uncertainty, AI allows markets to operate with both higher velocity and lower risk exposure. This represents a conceptual inversion of earlier thinking, where risk reduction was viewed as a constraint on efficiency. The findings show that risk reduction is now a mechanism of efficiency itself. This integration challenges the siloed structure of earlier literature, which treated market optimization and health security as separate agendas with separate tools. The review demonstrates that AI fuses these domains operationally, Shen and Zhang (2024) creating systems where health safeguards and economic performance advance together. This reframing is crucial because it positions AI not as a balancing compromise between two competing goals but as a unifying infrastructure that achieves both simultaneously, marking a fundamental shift from previous dualistic models.

Overall, the findings position AI as a systemic infrastructure that integrates production, logistics, surveillance, and regulation across agribusiness networks, contrasting sharply with earlier views of it as a collection of discrete tools (Hughes et al., 2021). Previous literature typically analyzed AI applications within narrow domains—production efficiency, supply chain management, or disease control—without exploring how they interact to reshape the overall structure of agro-food systems. The reviewed studies show that these domains are now interdependent through shared AI-driven data layers, enabling synchronized decision-making across borders and sectors (Parycek et al., 2024). This suggests that AI is no longer an incremental technology layered onto existing processes but a coordinating architecture that redefines how agribusiness systems function. Unlike earlier accounts that focused on bridging the

digital divide through connectivity, these findings show that the competitive and sanitary performance of global markets now depends on algorithmic intelligence rather than mere data access. This marks a transition from digitalization to intelligent integration. AI systems create unified operational environments where production forecasts inform logistics routing, bio surveillance informs market allocations, [Xu and Babaian \(2021\)](#) and compliance verification is embedded within routine flows. This integration enables real-time governance of both economic and health risks, which earlier frameworks did not conceive as achievable within a single system. Consequently, the findings recast AI not as a set of enhancements to agribusiness but as its emerging backbone ([Zador et al., 2023](#)). This shift from tool to infrastructure represents a conceptual break from earlier thinking and signals that AI is becoming the structural substrate on which modern agribusiness markets and biosecurity systems are jointly built.

CONCLUSION

The strategic application of artificial intelligence (AI) in agribusiness systems represents a transformative convergence of technological innovation, economic optimization, and biosecurity governance, offering a unified pathway to enhance market efficiency while mitigating zoonotic risks. Agribusiness operates through globally distributed networks that move agricultural products from production to consumption across borders, where fluctuations in supply, delays in logistics, and outbreaks of animal-borne diseases have historically destabilized markets and threatened public health. AI addresses these vulnerabilities by converting vast, heterogeneous data streams from farms, markets, transportation systems, and surveillance networks into predictive intelligence that guides real-time decision-making. Machine learning models forecast yields, detect anomalies in livestock health, optimize logistics routing, and anticipate market price shifts, thereby aligning production schedules with consumer demand and reducing surplus accumulation, price volatility, and post-harvest losses. Simultaneously, AI-driven bio surveillance systems analyze veterinary records, movement permits, genomic data, and informal signals from news or social media to identify emerging disease clusters days or even weeks earlier than traditional methods, enabling targeted containment actions that prevent widespread outbreaks and the economic disruptions they cause. Integrated into digital traceability platforms, AI verifies the origin, handling conditions, and sanitary compliance of goods, reducing fraudulent documentation, accelerating border clearances, and ensuring rapid recalls when hazards are detected, which reinforces trust among regulators, traders, and consumers. By embedding risk intelligence into the operational core of agribusiness, AI transforms regulatory compliance from a procedural hurdle into a flow-enabling infrastructure, linking market continuity to health security. Furthermore, when supported by interoperable data systems, shared governance frameworks, and institutional capacity, AI acts not as an isolated tool but as a systemic infrastructure that synchronizes production, logistics, surveillance, and certification across sectors and jurisdictions. This integration dissolves the long-assumed trade-off between efficiency and biosecurity, showing that risk mitigation can enhance rather than impede market performance, and positioning AI as the central coordinating architecture for resilient, transparent, and risk-aware global agribusiness systems.

RECOMMENDATIONS

To ensure the strategic application of artificial intelligence in agribusiness systems effectively enhances market efficiency while mitigating zoonotic risks, it is recommended that stakeholders pursue a coordinated, multi-layered implementation approach that integrates technological development with institutional and regulatory reforms. Governments, industry actors, and international organizations should invest in interoperable data infrastructures that connect farm management systems, logistics platforms, veterinary surveillance networks, and certification authorities, enabling seamless data flows essential for predictive modeling and real-time decision-making. Policies should mandate standardized data formats, labeling protocols, and event definitions to improve the accuracy and transferability of AI models across regions while embedding data privacy, security, and ownership safeguards to maintain trust. Dedicated capacity-building programs are needed to equip regulatory agencies, veterinary services, and market authorities with the analytical skills to interpret AI outputs and act on them within established sanitary and trade frameworks, ensuring that algorithmic insights translate into timely operational responses. Incentives such as subsidies, technical assistance, and digital inclusion initiatives should be targeted at smallholder producers and informal market actors to ensure their data are represented in training datasets, improving model fairness and reducing systemic blind spots in risk detection and market forecasting.

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