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Review

A systematic review on the impact of Artificial Intelligence in the agri-food supply chain

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ABSTRACT

With a growing global population and escalating concerns over food security, artificial intelligence (AI) has emerged as a transformative technology capable of optimizing agricultural processes and improving resource efficiency and security. This systematic review explores the transformative potential of artificial intelligence in the whole agri-food supply chain, focusing on its implications for agricultural productivity and consumer behavior. Using the PRISMA guideline, a total of 64 articles were selected to provide a comprehensive overview of the current state of research on artificial intelligence applications within this domain. Unlike previous reviews, this study leverages cluster analysis to categorize research findings into four main themes: 1) adoption of AI technologies in agriculture, 2) applications of AI in the intermediary management of the supply chain, 3) consumer perceptions and acceptance of AI-powered food innovations, and 4) the role of AI in precision nutrition and personalized health management. The review identifies key benefits of AI, including enhanced decision-making capabilities, improved supply chain transparency, and the facilitation of personalized nutrition strategies. It also highlights significant challenges such as technological accessibility, knowledge gaps among agricultural stakeholders, consumer skepticism, and notable methodological limitations in the existing research. The insights presented in this review contribute to a more comprehensive understanding of the AI's role in shaping the future of the agri-food supply chain and provide a foundation for policymakers, researchers, and industry stakeholders to develop strategies that maximize the societal and economic benefits of AI integration in the agri-food supply chain.

1. Introduction

Contemporary agri-food systems face unprecedented pressure to reconcile competing imperatives: nourishing a projected global population of 10 billion by 2050 (Krishnan et al., 2020; Kamyab et al., 2023) while advancing Healthy, Equitable, Resilient, and Sustainable (HERS) outcomes (Barrett et al., 2022). Climate volatility, resource degradation, and inequitable access threaten these goals, demanding transformative interventions. The urgency of systemic transformation is now irrefutable, as food systems sit at the nexus of climate change, malnutrition, and social inequities (Webb et al., 2020; Fanzo et al., 2022). Achieving such transformation requires a paradigm shift from linear, siloed thinking to a systems-science perspective that recognizes the interdependence of agriculture, health, and planetary boundaries (Hammond & Dubé, 2012). This calls for reimagining governance, roles, and responsibilities across public and private actors to ensure that food systems not only feed populations but also sustain cultures, livelihoods, and ecosystems. Artificial Intelligence (AI) is a technology with potential to reconfigure agri-food systems dynamics, yet its role in forwarding HERS objectives remains inadequately theorized and empirically fragmented.

In this context, it becomes essential to ask: what do we know about the current uses and impacts of AI within the agri-food system, and how well is this technology aligned with the normative goals of food system transformation? This study seeks to address this question by systematically mapping the existing empirical literature at the intersection of AI

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and the agri-food supply chain. To do so, it is first necessary to define what is meant by AI in this context. We adopt a broad and inclusive definition of AI as a collection of computational techniques and systems that enable machines to simulate aspects of human intelligence, such as perception, learning, reasoning, prediction, and autonomous decision-making (Radanliev, 2024). Specifically, we consider within scope the following AI approaches:

- Traditional AI, including rule-based expert systems and optimization algorithms;
- Generative AI that uses Large Language Models for text-based content and synthetic data generation (Hagos et al., 2024);
- Machine Learning, including supervised, unsupervised, and reinforcement learning models (Michelucci, 2024);
- Deep Learning and Neural Networks, used particularly for image recognition and pattern classification (Yaghoubi et al., 2024);
- Natural Language Processing for text interpretation, chatbot design, and sentiment analysis (Ong et al., 2024; Feuerriegel et al., 2025);
- Computer Vision and Image Processing, used in tasks such as crop monitoring, sorting, and quality control (Ghazal et al., 2024; Shehzad et al., 2025);
- Autonomous Robotics and Intelligent Agents, including both reactive and limited memory systems employed in harvesting, logistics, and food service applications (Hwa & Chuan, 2024).

While these AI approaches and technologies vary widely in design and purpose, they share a common goal: to enhance human decision-making or to automate complex tasks through data-driven learning and reasoning (Michael et al., 2024). In the context of agri-food systems, AI can act as a direct input into production processes (e.g., precision agriculture), as an intermediary tool that affects logistics and decision-making (e.g., demand forecasting), or as an exogenous enabler that reshapes actors' information sets, incentives, and capabilities (e.g., via predictive analytics or digital advisory services) (Deichmann et al., 2016). This multiplicity of roles requires careful contextualization in analyzing AI's potential and limitations.

Through a critical systematic review of the existing literature, we adopt a value-chain perspective by examining the application of AI across three core domains: primary production, intermediary management, and consumer-facing services, while also acknowledging the enabling role of governance and public policy. The agri-food supply chain is here conceptualized as the entire network involved in producing, processing, distributing, and consuming food, spanning from input providers and farmers to processors, retailers, and consumers.

Specifically, this systematic review aims to synthesize what is known about how AI is currently being adopted and studied within agri-food systems. In particular, it focuses on four thematic clusters identified through bibliometric and content analysis: (i) the adoption of AI in agriculture, (ii) applications of AI in the intermediary management of the agri-food supply chain, (iii) consumer perception of AI, and (iv) the role of AI in precision nutrition and personalized health management.

While other studies have separately analyzed these four aspects, to the best of our knowledge, this study stands out as the first systematic literature review providing a complete view of AI's transformative potential across the various stages of the agri-food supply chain. Additionally, unlike a superficial analysis of emerging technologies, the approach of this study relies on the use of the PRISMA guideline and cluster analysis to systematically categorize and synthesize the available results. Importantly, this review assesses the quality of the current research in the field, identifying key methodological strengths and limitations, and proposes guidelines to inform a future research agenda. By doing so, this review not only delineates the factors influencing AI adoption, but also provides a detailed framework to support researchers, industry practitioners and policy makers in the effective implementation of innovative solutions, regulations, and initiatives to enhance technical skills among farmers and other agricultural stakeholders.

2. Methodology

The methodology of this systematic review is structured into three main subsections. The research strategy outlines the databases searched, the search terms employed, and the inclusion and exclusion criteria applied to ensure the selection of relevant and high-quality studies. The quality assessment describes the criteria and procedures used to evaluate the methodological rigor and reliability of the included articles. Finally, the network analysis details the bibliometric techniques used to explore relationships among key concepts, authors, and institutions, providing a broader understanding of the research landscape.

2.1. Research strategy

The search string included the terms ("Artificial Intelligence" OR "decision support systems" OR "real time advisories" AND "technology adoption" AND "farmers" OR "consumer") OR ("Artificial Intelligence" OR "decision support systems" OR "real time advisories" AND "food supply chain" AND "Processing" OR "Distribution" OR "Retailing") OR ("Artificial Intelligence" OR "decision support systems" OR "real time advisories" AND "precision nutrition"). These terms were selected as the most representative keywords to identify relevant scientific contributions in the topic of AI integration in the agri-food supply chain. *Scopus*® and *Web of Science*® (WoS) databases were chosen to ensure the quality and scientific validity of the cited articles and reviews; these databases are recognized for their comprehensive and reliable sources. The searches in both databases were last conducted on July 15, 2025.

To ensure rigor, the systematic literature review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021). Fig. 1 presents a flow diagram of the search process, following the three steps suggested by PRISMA guidelines: identification, screening, and included studies. The diagram details the number of studies included or excluded at each step. Ultimately, 64 articles published between 2016 and 2025 were included in this review.

The search was conducted by filling in the fields "Article Title, Abstract, Keywords". The search was restricted to articles dating from 2016 to 2025. This timeframe was selected as AI is newly introduced and articles preceding this period have been excluded as these may not accurately capture the current landscape or provide clear and precise insights into the latest innovations and trends. The systematic search across the two databases yielded a total of 612 results. Before the formal screening, we excluded publications that did not meet the general inclusion criteria: full-text articles published in peer-reviewed journals between 2016 and 2025, written in English, and directly related to the adoption of AI in the agri-food supply chain. We excluded all other publication types (e.g., books, conference papers, reviews) and articles unrelated to the topic. Following this initial refinement, 291 articles proceeded to the screening phase. During this phase, duplicate articles between the two databases, articles unrelated to the specific focus of our study, and articles published in predatory journals were eliminated. Journals were considered predatory based on the Predatory journals (2025) list.[1]

To ensure a rigorous and transparent selection process, we complemented the general criteria with cluster-specific eligibility criteria, as detailed in Appendix A. The cluster-specific criteria focused on the content and scope of the studies, specifying the conditions for inclusion/exclusion within each thematic area of the review.Using both the general and cluster-specific criteria, 56 articles were retrieved via the two databases. Each of these articles was carefully evaluated through an in-depth eligibility assessment to ensure the studies' contextual relevance and alignment with its objectives. Eight additional articles were identified and included via other methods (i.e., citation and personal

[1] Source: https://www.predatoryjournals.org/the-list/journals.

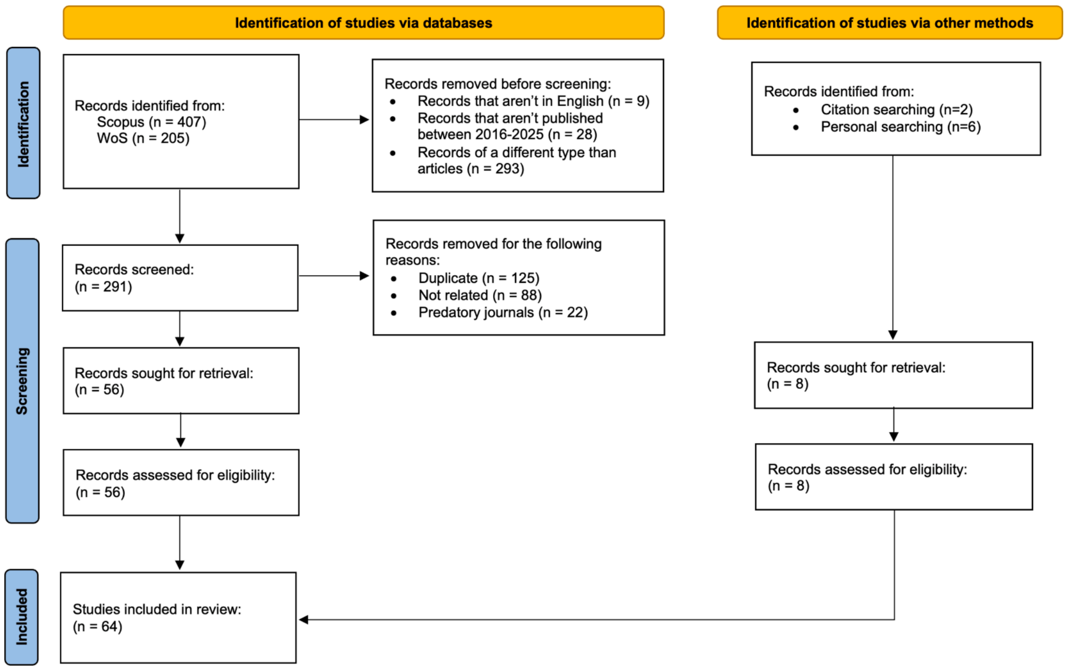

Fig. 1. PRISMA flow diagram for systematic reviews, which included searches of databases and registers only. Own elaboration following the PRISMA model.

searching). These articles were not initially found in the search results but were considered relevant because of their significant contribution to our understanding of the topic. This brought the total number of articles to 64, which were then subjected to qualitative analysis to explore the integration and impact of AI in the agri-food supply chain.

2.2. Quality assessment

We assessed the quality of the 64 studies included in this review using the National Institutes of Health (NIH) Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies (National Institutes of Health, 2016). Although the tool comprises 14 items, we selected 6 items most relevant to our review objectives; these address study population, exposure and outcome measures, and risk of bias. These items were chosen to ensure a consistent and focused evaluation across studies with diverse designs and reporting standards. The six items considered are:

Were all the subjects selected or recruited from the same or similar populations (including during the same time period)? (Variable coding: Selection Bias (1))
Were the inclusion and exclusion criteria for being in the study prespecified and applied uniformly to all participants? (Variable coding: Selection Bias (2))
Were sample size justifications, power descriptions, or variance and effect estimates provided? (Variable coding: Sample size)
Was the timeframe sufficient so that one could reasonably expect to observe an association between the exposure and outcome if one existed? (Variable coding: Timeframe)
Were the exposure measures (independent variables) clearly defined, valid, reliable, and implemented consistently across all study participants? (Variable coding: Exposure measures)
Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between the exposure(s) and outcome(s)? (Variable coding: Outcome)

Each study received one point for each question answered "yes" and zero otherwise, yielding a total score ranging from 0 to 6. Based on this score, studies were categorized into three quality levels: low quality (score 0–2), medium quality (score 3–4), and high quality (score 5–6). This scoring system facilitated a transparent and comparable assessment of methodological rigor across the reviewed literature (Yang et al., 2025a).

2.3. Network analysis

The network analysis performed with *VOS Viewer* identifies the most frequently used terms in the selected articles and their associations. It highlights the focal points of research related to AI in agriculture, AI in intermediary management, consumer perceptions of AI applications in agri-food systems, and AI in precision nutrition. The *VOS Viewer* software generates co-occurrence networks by quantifying the frequency and connections between terms appearing across articles, thus creating a visual representation of the research landscape. Each node in the *VOS Viewer* network represents a word or a set of a few words frequently used in the selected articles. The node size reflects the number of occurrences, while the links between nodes indicate co-occurrence relationships, highlighting the interconnectedness of different themes. Keywords are assigned to different clusters based on their co-occurrence patterns, with each cluster being distinguished by a unique color. This visualization facilitates the identification of prominent research themes and the exploration of their interconnections (Kirby, 2023).

3. Results

The presentation of the results is structured as follows: the outcomes of the bibliographic, keyword, and cluster co-occurrence analysis are provided in Appendix B. The cluster analysis revealed four main thematic groups within the literature—adoption of AI in agriculture, AI applications in intermediary supply chain management, consumer perceptions of AI in food systems, and AI in precision nutrition—which serve as the foundation for the detailed synthesis that follows. The results of the quality assessment are detailed in Appendix C; and the main information, characteristics, and findings of the articles included in this systematic review are outlined in Appendices D, E, and F respectively. The following section focuses specifically on synthesizing the current knowledge about the use of AI across the agrifood supply chain, as reported in the selected literature.

3.1. Cluster 1: Adoption of AI in agriculture

Despite growing enthusiasm for integrating AI and digital technologies in agriculture, it is imperative that claims regarding their effectiveness undergo rigorous scientific evaluation. Studies conducted in experimental settings have explored the technical potential of AI; for example, Darlan et al. (2025) show that deep learning models achieve high accuracy in classifying growth stages of greenhouse strawberries, promising optimized nutrient management. Similarly, simulations with decision support systems for agro-technology transfer suggest that targeted application of information could theoretically reduce the yield gap and improve productivity for many crops if practices were optimized (Debnath et al., 2018). Okayama et al. (2025) extend this potential to irrigation decisions in persimmon orchards, showing that convolutional neural networks trained on RGB (Red, Green, Blue) leaf imagery can achieve over 80 % accuracy in detecting water stress, offering a low-cost alternative to expensive soil moisture or infrared sensors. Linker (2021) also contributes to irrigation optimization by proposing a stochastic scheduling model that closely approximates ideal decisions based on perfect forecasts, better aligning with farmers' risk-averse reasoning. However, both studies emphasize the increased computational burden of AI tools, suggesting that scalable implementation may depend on accessible, cloud-based platforms. While these findings are robust within their experimental or predictive contexts, they represent projections of benefits derived from ideal conditions or niche applications and do not always translate directly into large-scale outcomes in real agricultural settings. This gap is echoed by Rose et al. (2018), who demonstrate that farmers and advisors often resist or reinterpret decision support tools, preferring experiential knowledge and local trust networks over impersonal digital systems. Similarly, De Oliveira et al. (2022) show that compliance-driven innovation, such as the adoption of decision support systems for regulatory purposes, faces barriers related to usability, maintenance, and trust in data-sharing institutions. Although design-thinking approaches can improve adoption, farmers remain wary of granting control to external actors, preferring universities and farmer associations over commercial companies.

Evidence from simulation-based studies also underscores the technical promise of integrated decision frameworks. Clarke et al. (2017), using an integrated decision support system in Ethiopia, assess the combined impacts of modern technologies on productivity, on-farm income, and nutrition at watershed and farm scales. Results indicate improvements in output —specifically higher yields of grain and associated forage—and notable increases in household income. However, the authors caution that these estimates remain coarse approximations due to limited spatial specificity and potential downstream socio-ecological impacts.

The literature reveals that claims of positive impacts from survey-based and modeling studies are often linked to stakeholder perceptions and modeled correlations. Prasad et al. (2025), through a Partial Least Squares Structural Equation Modeling (PLS-SEM) of famer perceptions in India, conclude that AI-enabled smart farming[2] significantly improves agricultural productivity and contributes to rural development, with productivity partially mediating this relationship. Likewise, Kitole et al. (2024) assess the impact of digitalization on the well-being of smallholder farmers in Tanzania, operationalized through farmers' income as a quantitative indicator of welfare. They find that digital adoption affects farmers' income, reflecting perceived improvements in access to extension services, pest management, and market information. Wang et al. (2024a), using survey data in China, find that adoption of digital technologies, including AI, significantly promotes technological innovation in cereal production. Specifically, they find that digitalization enocurages innovations that enhance precision and intelligent production management, optimize resource allocation through data-driven decision-making, and support the transition from extensive to intensive, smart farming systems. Oyinbo et al. (2022), through a randomized controlled trial in Nigeria, find that site-specific fertilizer recommendations combined with price risk information increase maize yields and net returns, but skewed toward wealthier farmers, reflecting liquidity constraints and risk aversion. These findings resonate with Paltasingh and Goyari (2018), who demonstrate that education significantly influences agricultural productivity—measured as paddy yield in kilograms per hectare— only when paired with modern technology adoption, highlighting the complementary role of human capital.

The litereture assessment above highlights that the effectiveness of AI and the opportunity for public investment in this sector are often conditioned by non-technical factors such as lack of AI trustworthiness. For instance, Alexander et al. (2024) reveal how low-quality industrial products have eroded farmers' trust, making it difficult to adopt more reliable technologies, and highlight the complexity in defining responsibility for trustworthy AI. Bekee et al. (2024) confirm farmers' skepticism toward commercial companies perceived as profit-focused, while Czibere et al. (2023) identify low education, inexperience, and lack of awareness of benefits as primary barriers to adoption of precision agriculture technologies in Hungary, noting that farmers often do not perceive a clear return on investment. Dela Rue et al. (2019) add nuance by showing that dairy farmers in New Zealand strongly prefer automation technologies (e.g., automatic cup removers, teat spraying, and drafting) over decision-support tools, especially in large, modern rotary milking parlors. While automation technologies are associated with an increase in labor efficiency, data-capture tools are less appreciated, with low adoption and satisfaction, often due to unclear or difficult-to-measure financial returns. This reflects a broader pattern: technologies that deliver immediate, visible benefits are favored over those requiring interpretive engagement or long-term vision.

Adoption in emerging economies also faces unique structural constraints. Kaushik and Rajwanshi (2023), using interpretive structural modeling, examine the adoption of Precision Dairy Farming technologies in India[3]—including systems for animal identification and monitoring (RFID-based), automated milking, data management, and artificial insemination—and identify experience in dairy farming, competitive pressure, and digital literacy as key enablers for technology uptake. However, low yields, small herd sizes, labor shortages, and high capital costs continue to hinder adoption. The authors stress the need for awareness-raising, training, and workforce development to support sustainable integration. In Ghana, Martey et al. (2023) find high willingness-to-pay for a low-cost irrigation scheduling tool, especially among women and youth farmers. Yet, field trials show higher yields in traditionally irrigated fields, raising concerns about user perceptions and the actual agronomic effectiveness of the tool, highlighting again the necessity of pairing innovation with education and contextual adaptation.

Tascione et al. (2024) demonstrate through Life Cycle Assessment studies that smart farms do not always show better environmental performance compared to traditional farms, and that mere technological implementation can shift environmental burdens or even worsen impacts due to lack of managerial awareness. This suggests that investments in AI require a holistic understanding of interactions with farming practices and the environment, not mere technological integration. Some studies suggest that the effectiveness of AI tools in agriculture is not universal but highly dependent on context, proving most beneficial under dynamic market cycles characterized by fluctuating prices, evolving weather conditions, and changing production practices

[2] Smart farming consists of digitally integrated farming systems that use sensors, automation, and data analytics to optimize agricultural processes (Mahto et al., 2024).

[3] Precision Dairy Farming is the use of digital technologies and data-driven tools to monitor, manage, and optimize dairy herd health, productivity, and farm efficiency in real time (Kaushik and Rajwanshi, 2023).

(De La Peña & Granados, 2024). In these settings, AI systems add value by providing real-time, adaptive, and context-specific recommendations that help farmers respond quickly to market and environmental shifts.

Regarding public expenditure, evidence indicates that estimated gains from AI are potentially significant but unevenly distributed and dependent on complementary investments. Wang et al. (2024a) provide concrete data on benefit distribution, indicating that digital technology has the greatest impact on low-income farmers, suggesting potential to reduce rural inequalities. This constitutes strong evidence supporting public spending on equity and inclusion grounds. However, Hong et al. (2023), through numerical modeling, show that adoption of green technologies is not always the preferred choice for farmers even when accompanied by subsidies, and that wholesale prices are not necessarily higher for adopters, challenging automatic returns on investment based solely on technology. This implies that public investments in AI should be accompanied by targeted training programs (Czibere et al., 2023; Gyawali et al., 2023), improvements in digital infrastructure (Al-Ammary and Ghanem, 2024; Deji et al., 2024), and mechanisms to build and maintain trust through transparency and independent performance validation (Alexander et al., 2024; Bekee et al., 2024). Moreover, as Rose et al. (2018) argue, developers and funders must consider social and cultural impacts alongside productivity and environmental metrics, recognizing that AI and digital tools reconfigure, and not merely optimize, farmers' identities and everyday practices. Without these supporting measures, the effectiveness of AI investments risks falling short of their full potential or generating simulation artifacts that cannot be replicated in real agricultural contexts.

3.2. Cluster 2: Applications of AI in the intermediary management of the agri-food supply chain

In the context of intermediary management of agri-food supply chains, the application of AI emerges as a key area of scientific research and development, with significant claims regarding its potential impacts on operational efficiency, food safety, and sustainability. However, a critical evaluation of the existing literature requires distinguishing between conclusions supported by rigorous empirical evidence, those derived from simulations or researcher-controlled studies, and those that primarily reflect industry viewpoints or perceptions.

Several studies provide robust support for many of the claims about AI's impact in intermediary management of agri-food supply chains. For instance, the quantitative study by El Bhilat et al. (2024), employing PLS-SEM on executives and managers in the Moroccan agri-food industry, offers statistically significant evidence that AI integration directly and positively influences distribution network efficiency and, through mediation, the overall efficiency of the agri-food supply chain and organizational performance. The validity and reliability of these conclusions are confirmed by rigorous metrics, all well above acceptable thresholds. Similarly, Jain et al. (2021) apply PLS-SEM on professionals and academics in the Indian food sector and confirm a significant relationship between AI adoption and improved operational efficiency, understood as resilience, integration, and transparency. Although these studies rely on perception data collected via surveys, their analysis using advanced statistical methods provides a solid empirical foundation for their conclusions.

Regarding specific AI applications, Makridis et al. (2022) present a deep learning approach combining natural language processing and time series forecasting for predicting food recalls. This study evaluates the performance of models (DeepAR, Simple Feed Forward, Seasonal WaveNet, and a Reinforcement Learning model) using well-defined metrics on a proprietary food recall dataset. The use of surrogate data to enrich the dataset and the analysis of results in terms of Mean Squared Error confirm that the Reinforcement Learning-based approach can outperform other models in specific scenarios, suggesting concrete predictive improvements. Similarly, Buyuktepe et al. (2025) focus on the interpretability of deep learning models for food fraud detection through Explainable AI tools such as LIME, SHAP, and WIT. Although the study does not provide a global numerical performance metric, it reports an evaluation of the deep learning model's predictive capabilities and an in-depth analysis of the interpretability of its decisions. Parallel to these developments, several studies focus on AI and decision support systems for managing perishability, safety, and logistics. Ktenioudaki et al. (2022) leverage hyperspectral imaging to predict strawberry shelf-life, enabling non-destructive quality assessment that supports strategic planning and waste reduction. Similarly, Leithner and Fikar (2019) show how integrating shelf-life data into logistics models can minimize food losses by reallocating surplus inventory to alternative distribution channels. Violi et al. (2023) extend this logic with a dynamic inventory-routing model that accounts for stochastic demand and product aging, achieving cost reductions while reducing spoilage.

Food safety management also benefits from decision support systems integration. Gogichaishvli et al. (2022) propose an AI algorithm based on logistic regression to predict the safety of perishable product deliveries. Furthermore, Van der Fels-Klerx et al. (2022) introduce a system that combines pre- and post-harvest knowledge with real-time CO_2 sensor data to monitor mycotoxin risks in silos to facilitate early warning alert interventions. These developments illustrate the convergence of AI with Internet of Things (IoT)-enabled monitoring for proactive risk mitigation.

Sustainability considerations are addressed through optimization frameworks that incorporate environmental objectives. Mogale et al. (2020) propose a bi-objective mathematical model minimizing both costs and CO_2 emissions in grain distribution systems. Similarly, circular economy approaches such as the feed conversion model by Suckling et al. (2021) demonstrate how decision support systems can valorize food waste to enhance economic returns while reducing environmental impact. Yang et al. (2025b) offer an in-depth analysis of AI's role in green supply chains. The study concludes that AI adoption can have contrasting impacts on profits depending on whether the retailer underestimates or overestimates consumer green preferences.

Other strands of research explore last-mile logistics and short food supply chains. Cramer and Fikar (2024) and Melkonyan et al. (2020) emphasize the role of crowd logistics platforms in expanding market reach for small farmers while balancing trade-offs in travel distances and food quality. Calzavara et al. (2023) further analyze e-grocery distribution strategies by showing how order volume, customer behavior (e.g., click-and-collect), and product perishability influence the optimal design of supply chain networks.

AI-driven planning and uncertainty management also feature prominently in recent work. Flores and Villalobos (2019) integrate stochastic optimization with machine learning techniques such as Support Vector Machines to predict yield potential based on environmental models rather than historical production data. Wang et al. (2024c) propose a hybrid interval-valued fuzzy method to rank barriers to resilient food supply chains, identifying small and medium-sized enterprises as facing the most severe constraints.

Despite these advancements, significant adoption barriers persist among supply chain intermediaries. Studies consistently identify financial constraints, lack of public investment, and high implementation costs as critical obstacles (El Bhilat et al., 2024; Wang et al., 2024b). Data privacy concerns also remain a major barrier in food supply chain finance (Wang et al., 2024b), while organizational inertia and fragmented regulatory frameworks further complicate large-scale integration.

The most thorough analysis of the magnitude and distribution of AI-derived gains comes from Yang et al. (2025b). This study warns that benefits from AI adoption may be outweighed by adoption costs, emphasizing the need for careful evaluation. Their model demonstrates that AI gains are unevenly distributed and can involve trade-offs among supply chain actors and social welfare. For instance, AI adoption may increase retailer profits but potentially reduce those of producers, or vice versa, and have variable impacts on social welfare and environmental benefits depending on market conditions and costs. This evidence can be interpreted as implying that public spending should not be based on simple assumptions of generalized benefits but requires detailed understanding of the distribution of gains and losses among stakeholders in the supply chain and multidimensional impacts (economic, social, environmental). Compensation mechanisms may therefore be necessary to secure participation and fair distribution of benefits.

In summary, while AI offers promising capabilities to improve operational efficiency, food safety and quality, and early warning systems for risk detection, claims regarding its economic and sustainability benefits remain less substantiated. The literature suggests the necessity of complementing technological innovation with policies that ensure equity and sustainability, mitigate specific barriers, and consider overall social welfare impacts.

3.3. Cluster 3: Consumer perception of the use of AI in the agri-food supply chain

Research on consumer adoption of AI in the agri-food sector constitutes a dynamic and interdisciplinary domain. It involves a complex interplay of cognitive, emotional, and contextual factors that shape individual and collective responses to AI-enabled technologies. Across the literature reviewed, consumer acceptance is commonly presented as a balance between perceived benefits (e.g., utility, convenience, novelty) and perceived risks (e.g., privacy, loss of control, unnaturalness). In this section, we assess the current state of evidence, distinguishing between robust empirical findings and claims that remain speculative, simulation-based, or derived from industry narratives lacking rigorous validation.

A central finding emerging across multiple studies is the pivotal role of perceived usefulness in shaping consumer intentions to adopt AI technologies. ElSayad and Mamdouh (2024), using a structured survey with Egyptian millennials, demonstrate that perceived usefulness significantly mediates the influence of consumer optimism and innovativeness on AI-based purchase intentions, including the purchase of food products. Similarly, Arce-Urriza et al. (2025) employ PLS-SEM to show that familiarity with AI systems (such as generative chatbots) increases trust and reduces perceived risk. These findings suggest that experiential learning and exposure are key enablers of AI acceptance, consistent with the Theory of Reasoned Action (Arce-Urriza et al., 2025). In line with this, (Silalahi, 2025) highlights that trust plays a central role in shaping consumers' engagement with generative AI, emphasizing that both cognitive factors (e.g., perceived information quality and usefluness) and affective factors (e.g., anthropomorphism and interaction quality) jointly determine sustained adoption. This multidimentional view of trust futher supports the notion that AI acceptance in the agri-food domain cannot be fully understood without considering the interplay between rational and emotional mechanisms.

Beyond rational cost–benefit evaluations, the consumer experience of interacting with AI technologies has emerged as a multidimensional construct of growing importance. Wang et al. (2024d) identify five key dimensions of AI-enabled customer experience (e.g., data acquisition, classification, delegation, social experience, and anthropomorphism) validated through confirmatory factor analysis. Notably, anthropomorphism alone accounts for a big part of the variance in behavioral engagement, indicating that human-like characteristics in AI agents can significantly shape user behavior. Frank et al. (2021), through a multi-country survey, further demonstrate that status-related and hedonic (pleasure-oriented) values outweigh utilitarian motivations in the early stages of adoption, particularly for highly autonomous technologies. These findings challenge utilitarian frameworks and underscore the importance of emotional and social drivers in adoption pathways.

Perceived risk remains a substantial inhibitor to adoption. Sohn (2024) develops a comprehensive framework consisting of nine risk dimensions and shows, through a PLS-SEM, that fears related to dependency and societal spillover effects are especially salient for autonomous AI systems. Complementing this, Giacalone and Jaeger (2023) highlight the role of food technology neophobia as a significant barrier: their multi-country study reveals that perceived unnaturalness can reduce consumer acceptance of AI-enhanced food products. These studies, based on large-scale representative samples and hierarchical modeling, offer strong external validity and indicate that techno-skepticism remains pervasive, especially in food-related contexts.

However, some claims in the literature require more cautious interpretation. For example, the transparency of AI systems is often suggested as a universal trust-building mechanism, yet evidence remains that they are context-dependent. Wang and Qiu (2024) find that disclosing the artificial nature of digital endorsers increases consumer engagement via perceived agency. Nonetheless, their experiments are limited to artistic products and users with prior AI exposure, raising questions about generalizability to broader domains such as food retail. Similarly, the often-cited claim that AI leads to lower prices (Subbaiah, 2024) lacks empirical grounding in demand elasticity, willingness to pay, or long-term consumer surplus. These assertions risk being conflated with industrial promotion rather than scientific assessment.

Cultural and demographic variables play a decisive role in mediating AI adoption. Giacalone and Jaeger (2023) apply hierarchical clustering to reveal significantly higher acceptance rates of AI food technologies in India compared to Western countries, which they attribute to differing regulatory frameworks and socioeconomic contexts. Furthermore, the level of automation appears to recalibrate decision-making priorities. For example, Frank et al. (2021) show that higher autonomy in AI systems reduces the weight of utilitarian concerns while increasing hedonic value salience, highlighting the shifting nature of consumer preferences depending on technological sophistication.

Temporal dynamics add further complexity to adoption behavior. Silayach et al. (2025), in a longitudinal study analyzing 150,000 app reviews from 2017 to 2024, find that the COVID-19 pandemic significantly altered user expectations: demand for authenticity in AI companions rose post-2020. This combination of big data analytics and qualitative methods (e.g., focus groups) offers evidence for the fluid and event-sensitive nature of consumer perceptions, which can influence when users connect with AI companions, as some have reported doing after dinner.

Despite these valuable insights, the literature reveals a critical gap. The overall economic impact of AI on consumers remains underexplored. While some studies identify perceived cost as a barrier (e.g., Sohn & Kwon, 2020), no research systematically quantifies price elasticity, data-driven price discrimination, or the redistribution of consumer surplus. This omission is notable given the growing relevance of algorithmic pricing and behavioral targeting in the agri-food sector. Without such analysis, it is difficult to assess whether AI delivers net benefits or exacerbates power asymmetries and inequities.

In conclusion, research on consumer adoption of AI in the agri-food domain has built a robust foundation around cognitive and emotional drivers (e.g., perceived utility, trust, hedonic value) and well-documented barriers (e.g., risk, complexity). The strength of evidence however varies significantly across studies: while many offer statistically sound, externally valid findings, others rely on simulations or industry-driven narratives with limited generalizability. Key priorities for future research include the development of economic frameworks for evaluating AI's impact on consumer welfare; the adoption of interdisciplinary, mixed-method approaches; and an explicit focus on policy instruments to ensure ethical and inclusive AI diffusion. Only by integrating methodological rigor with critical reflection on consumer interests can the scientific community meaningfully inform the development and governance of AI in food systems.

3.4. Cluster 4: Precision nutrition and personalized health management

In the emerging landscape of personalized nutrition, AI integration represents a significant but still largely unexplored opportunity to make dietary interventions more precise, accessible, and adaptable to individual needs. However, our critical review of recent literature sources suggests that despite the enthusiasm, the reliability and maturity of AI technologies applied to nutrition remain uneven and often affected by limitations, which we explore in more detail below.

Several studies shown how generative AI tools, such as large language models, can provide detailed dietary recommendations, but with inconsistent and sometimes inaccurate results. Agne and Gedrich's (2024) comparative analysis reveals major limitations in the nutritional suggestions provided by ChatGPT, including errors in nutritional values, difficulties in linking specific nutrients to real foods, and poor reproducibility among responses. A similar issue emerges in Bayram and Arslan (2025)'s study, in which multiple AI models, including ChatGPT-4, Claude and Mistral, show difficulties in adhering to predetermined caloric and nutritional constraints for popular diets, generating outputs that are often discordant with each other (Agne and Gedrich, 2024). These results suggest the need for more standardized and structured input queries, integration of validated dietary databases, and transparency about model data sources, aspects still lacking in most of the instruments analyzed.

On the clinical side, the results tend to be more promising. Connell et al. (2023), as well as Karakan et al. (2022) and Tunali et al. (2024), document clinically significant improvements in gastrointestinal symptoms, risk of type 2 diabetes, and quality of life in patients undergoing precision nutrition interventions based on microbiome data and AI algorithms.

The use of AI in precision nutrition is not limited to the generation of recommendations, but also extends to data collection and management. In this context, Lacruz-Pleguezuelos et al. (2025) demonstrate the feasibility of using wearable devices and automated tools in nutrition counseling and weight monitoring. Participant adherence, quantity and quality of data collected, and effective integration with AI systems indicate that the use of wearable technologies may be a key component of future precision nutrition. Romero-Tapiador et al. (2023) present a public database that centralizes food images, data from wearables, questionnaires, and biological samples from the same intervention in a standardized manner. They find that the quality and interoperability of the database is a major strength, but data collection is subject to inherent errors in self-reported methods or partial images.

On the technology front, the application developed by Saad et al. (2025) demonstrates the potential of AI in identifying and classifying foods using real-time images. The use of advanced computer vision algorithms enables accurate classification even in the presence of partial occlusions, while integration with personalized chatbots enhances the user experience. However, the scalability of the system remains a challenge, as does its applicability to very different culinary contexts. Another innovative approach in the technology front is that proposed by Feng et al. (2023), who design a controlled trial to test an AI-based smartphone app capable of providing real-time dietary assessments. The value of this study lies in the intent to translate the intervention into a real-world scenario, while acknowledging limitations related to the language context (only available in Chinese) and tracking of meals consumed outside the study's control.

From the perspective of prediction and prevention, the application of machine learning in public health contexts has been illustrated by Constenla-Villoslada et al. (2025), who use early warning models to identify the risks of acute childhood malnutrition based on dynamic and remote sensing data and subsequent targeting of food assistance. This study stands out for its methodological rigor and large-scale validation. The approach highlights how data quality and frequency are crucial to the predictive reliability of AI models in nutritionally sensitive domains. Complementing these results, Janssen et al. (2025) demonstrate the predictive power of machine learning models for malnutrition risk in neonatal intensive care units. They find that Generalized Linear Models with Elastic Net Regularization achieve the best performance for weight prediction, while Extreme Gradient Boosting leads in classification tasks. Importantly, Extreme Gradient Boosting maintains strong performance even after a reduction in input features, highlighting its efficiency for clinical use. Nevertheless, Janssen et al. (2025) acknowledge that generalizability remains limited by the single-center design and the complexity of integrating such models into routine practice, particularly when some critical variables still rely on invasive or resource-intensive procedures.

Overall, while there is a shared enthusiasm for the potential of AI in precision nutrition, it seems clear that the currently available solutions are not yet mature enough for widespread clinical adoption. AI models show promising potential but also structural errors that undermine their reproducibility and reliability. Recurring limitations-from variability in outputs, to a lack of transparency in data, to the low methodological quality of some trials indicate that, rather than replacing clinical experience, AI should currently be considered a supporting tool, to be complemented by human intervention. At the same time, it is crucial to incentivize rigorous, multicenter, transparent and independent studies to more robustly test the effectiveness of existing tools.

4. Discussion

A key pattern emerging across the literature is that AI adoption is mediated less by technical performance and more by behavioral, institutional, and economic factors. Farmers' skepticism toward commercial providers, coupled with their reliance on experiential knowledge and local trust networks, reveals a critical trust deficit that technology design alone cannot solve. This highlights the need for institutional innovations alongside technological ones, such as third-party validation systems, cooperative-led technology dissemination, and public certification of AI tools. Moreover, the evidence that wealthier farmers disproportionately benefit from site-specific recommendations (Oyinbo et al., 2022) highlights a distributive dilemma. Public investment in AI should therefore be linked to pro-poor targeting strategies, possibly through tiered subsidy programs, microcredit for technology adoption, and farmer training initiatives that build digital literacy.

Economic asymmetries in the distribution of AI-derived benefits further underscore the need for recalibrated policy design. Evidence from Yang et al. (2025b) suggests that downstream actors—retailers and logistics firms—capture substantial gains through predictive analytics for inventory management and demand forecasting, whereas primary producers bear higher costs and uncertain returns. These imbalances have systemic implications: if upstream actors face persistent disadvantages, technology adoption may stall, weakening efficiency improvements in midstream and downstream operations. To mitigate this, policy instruments should move beyond blanket subsidies and adopt conditional, performance-based mechanisms that link public support to multidimensional outcomes, such as reductions in food waste or measurable improvements in farmer income.

Environmental sustainability, a central component of the HERS framework (Barrett et al., 2022), emerges as another critical area of tension. While AI is often presented as a sustainability enabler, evidence from life cycle assessments (Tascione et al., 2024) indicate that automation and sensor-intensive systems may increase energy and material demands, potentially offsetting emissions reductions from improved resource efficiency. These trade-offs propagate along the supply chain: energy-intensive production systems increase the carbon footprint of processing and distribution stages, undermining net gains in sustainability. Consequently, policy frameworks should adopt a systems perspective and mandate environmental audits for AI-based interventions while incentivizing designs aligned with circular economy principles. Without such measures, rebound effects could jeopardize global climate commitments, especially in regions reliant on carbon-intensive energy sources.

The literature also points to the role of anthropomorphism in shaping user engagement with AI agents (Wang and Qiu 2024; Wang et al. 2024b; Wang et al., 2024c; Arce-Urriza et al., 2025; Silayach et al., 2025). While human-like characteristics can enhance perceived familiarity and trust, excessive realism may backfire. This is consistent with the Uncanny Valley theory (Mori et al., 2012), which posits that people's emotional response to humanlike robots shifts from empathy to discomfort when the appearance approaches, but fails to fully achieve, a lifelike form. Such insights suggest that in designing AI-based interfaces for agri-food applications, developers should balance human-like cues with functional clarity to avoid triggering adverse reactions.

In the domain of nutrition, AI-driven personalized interventions illustrate both the transformative potential and structural limitations of digital health innovation. Applications like microbiome-based dietary recommendations and predictive models for malnutrition offer clinical promise, yet they remain constrained by data dependency, infrastructural demands, and algorithmic bias (Connell et al., 2023; Janssen et al., 2025). These limitations are particularly acute in low-resource settings, where malnutrition burdens are greatest, amplifying risks of exacerbating health inequalities rather than alleviating them. This directly relates to the equitable dimension of the HERS framework, which emphasizes reducing disparities and ensuring fairness across populations. In this context, AI, especially when integrated with other emerging digital technologies, is gaining attention for its potential to enhance food security and supply chain transparency (Reitano et al., 2024). Recent evidence illustrates how AI can also be leveraged to address food insecurity and malnutrition in ways that promote more targeted and equitable interventions. For example, AI-based early warning systems, such as the model developed by Constenla et al. (2025), have demonstrated the ability to predict child acute malnutrition months in advance, enabling geographically precise targeting of humanitarian food assistance to the most vulnerable communities. Similarly, a systematic review by Yang et al. (2025a) highlights applications of AI in food bank and pantry operations, including forecasting in-kind donations, optimizing collection routes, and improving inventory management to enhance equitable food redistribution. At the individual level, Bailey et al. (2024) emphasize the potential of AI tools such as digital twins to refine predictive nutrition models by incorporating underrepresented genetic, demographic, and microbiome data, thereby reducing bias and extending the reach of precision nutrition to underserved groups. Addressing these challenges requires investments that extend beyond digital tools that could strengthen primary healthcare, ensure equitable access to diagnostics, and implement ethical frameworks for health data governance. Regulatory oversight must also ensure transparency and inclusivity in data collection to avoid perpetuating biases that disadvantage vulnerable populations.

Across the whole agri-food supply chain the findings converge on a critical insight: the transformative potential of AI is contingent on complementary investments in human capital, governance, and infrastructure. For policymakers, this calls for integrated strategies that move beyond technological determinism. Key priorities could include developing interoperable data standards and open-access platforms to foster trust and reduce vendor lock-in; designing ethical and legal frameworks that safeguard equity and privacy; promoting participatory design and digital literacy initiatives to align innovation with user needs; and implementing impact evaluation protocols that capture economic, social, and environmental dimensions rather than focusing solely on yield or efficiency metrics. By reframing AI adoption as a socio-technical transition rather than a purely technological upgrade, policy can play a decisive role in steering innovation toward inclusive, sustainable, and resilient food systems.

5. Conclusion

The integration of AI into the agri-food supply chain is reshaping the landscape of many fields by introducing innovative solutions that enhance productivity, sustainability, and health outcomes. The evidence from this systematic review illustrates the transformative potential of AI in optimizing resource allocation, enabling personalized nutrition strategies, and improving supply chain transparency. However, realizing the full potential of these technologies requires overcoming significant barriers related to infrastructure, policy support, consumer trust, and data governance.

Future research and policy initiatives should focus on overcoming existing barriers to ensure equitable access and sustainable adoption of AI. There is also a need to develop inclusive and adaptive solutions for diverse populations and refine the regulatory frameworks to balance innovation with responsible usage. Furthermore, current research on AI in the agri-food sector often lacks methodological rigor, being predominantly based on short-term interventions and effects, and is frequently underpinned by limited or absent theoretical frameworks to guide the study of AI adoption and its impacts on the agri-food chain. Collaboration between governments, industries and researchers is critical to promote the adoption of these technologies in a responsible way and create a more sustainable, safe and equitable food system for all.

CRediT authorship contribution statement

Matilde Reitano: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Michelle S. Segovia:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision. **Rodolfo M. Nayga:** Writing – review & editing, Validation, Supervision, Funding acquisition, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2025.102983.

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