The Journal of Asia Entrepreneurship and Sustainability RESEARCH ARTICLE

The Role Of Artificial Intelligence In Promoting Sustainable Supply Chains Across The Food Industry:Evidence From Agriculture, Manufacturing And Fast-Food Retail In India

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Abstract
This paper examines how Artificial Intelligence (AI) is reshaping sustainable supply chain management (SSCM) across the food sector, with particular attention to consumer-facing implications for India's fast-food industry. As environmental and ethical concerns increasingly influence purchasing decisions, AI capabilities — demand forecasting, waste-reduction systems and intelligent logistics — are changing how food businesses source, produce and distribute their products. Synthesizing evidence from more than 120 academic and industry sources published between 2015 and 2022, the review traces AI's footprint across four connected stages of the food value chain: agricultural production, manufacturing, supply-chain logistics and consumer engagement. The evidence indicates that AI-enabled SSCM strengthens consumer trust, lifts operational efficiency and supports environmental accountability, positioning it as a meaningful lever for long-term sustainability in food retail, including fast-food operations.

Keywords: Impact of Artificial Intelligence; Sustainable Supply Chain Management; Fast-Food Industry; Consumer Behaviour; Sustainability; India

1. Introduction

The global food system is under growing pressure to produce more while consuming less. The Food and Agriculture Organization estimates that output will need to rise by roughly 70% by 2050 to keep pace with population growth (FAO, 2017), even as climate change, land degradation and water scarcity constrain traditional production methods and consumers demand greater transparency and safety (Rockström et al., 2017). Artificial Intelligence offers a materially different way of managing this pressure. Unlike conventional rule-based software, AI learns statistical patterns directly from data, which allows it to adapt its predictions and recommendations as conditions change (Russell & Norvig, 2016). Techniques such as machine learning, deep learning and natural language processing are now present at almost every stage of the agri-food value chain — from optimizing fertilizer and pest-control inputs on the farm, to streamlining processing operations and logistics, to personalising nutrition guidance for individual consumers (Goodfellow et al., 2016).

This paper draws together the existing evidence on AI's role in food systems, examining the technologies in use, their strategic consequences for different industry actors, and the ethical questions they raise. The aim is to give practitioners, policymakers and researchers a structured view of both the opportunities and the risks that come with AI-driven transformation of food supply chains (Tzachor et al., 2022).

India's food industry stands at the intersection of enormous scale and mounting sustainability pressure. As one of the world's largest agricultural economies, the country loses a substantial share of its harvest to inefficient supply chains, weak coldchain infrastructure, and fragmented information flow between farm, factory, and final consumer. Supply chain management can be optimized to prevent food wastage, as artificial intelligence can be used to tackle the inefficiency of primitive supply chains, with startups such as LogiNext and Locus.sh already working to improve efficiency across the journey from farms to manufacturing units to retail markets. The scale of the opportunity is significant: McKinsey has estimated that efficient use of artificial intelligence to prevent food wastage represents an economic opportunity worth $127 billion by 2030, underscoring why AI adoption in food supply chains has moved from a peripheral efficiency tool to a strategic sustainability imperative. investindiainvestindia

Artificial intelligence is increasingly positioned as a structural solution to these long-standing supply chain inefficiencies rather than a marginal add-on. The integration of AI in agricultural supply chains represents a paradigm shift that significantly enhances efficiency across various stages of the value chain, offering advanced

analytics and decision-support tools that streamline operations and contribute to improved sustainability. In practical terms, AI-driven predictive modelling helps optimise transportation routes and reduce post-harvest losses, while smart logistics systems enable real-time monitoring of inventory and demand fluctuations that reduce waste. Beyond logistics, machine learning models analyse historical data to predict market trends, improving procurement, production and distribution decisions and reducing the risk of overstocking or stockouts, while AI combined with technologies such as blockchain supports farm-to-consumer traceability, reinforcing food safety and consumer trust in the sustainability credentials of products. Harnessing Artificial Intelligence for Sustainable Agricultural Development in Africa: Opportunities, Challenges, and Impact +3

Within India specifically, empirical evidence on AI adoption is beginning to accumulate across the food value chain. At the primary production stage, Prasad et al. (2025), using Partial Least Squares Structural Equation Modelling of farmer perceptions in India, found that AI-enabled smart farming significantly improves agricultural productivity and contributes to rural development, with productivity partially mediating this relationship. Similarly, Kaushik and Rajwanshi (2023) examined the adoption of precision dairy farming technologies in India—including RFID-based animal identification, automated milking and data management systems—and identified farming experience, competitive pressure and digital literacy as key enablers of technology uptake. On the demand side, Giacalone and Jaeger (2023) found significantly higher consumer acceptance of AI-based food technologies in India compared with Western countries, attributing this to differing regulatory frameworks and socioeconomic contexts. Government policy has reinforced this momentum: schemes such as the Pradhan Mantri Kisan Sampada Yojana (PMKSY) provide grant-based financial support for integrated cold-chain and value-addition infrastructure, creating the institutional scaffolding on which AI-enabled logistics can operate. A systematic review on the impact of Artificial Intelligence in the agri-food supply chain - ScienceDirect +3

At the manufacturing and processing stage, the potential gains are similarly substantial, with reported operational improvements including reduced labour costs and marked efficiency gains in logistics and inventory management through AI-driven analytics, with AI-driven analytics achieving up to 95% optimisation in supply chain efficiency, logistics and inventory management, alongside a 30% reduction in labour expenses in some operations. Large Indian conglomerates have begun to operationalise this potential: for instance, ITC has applied AI-based analytics to manage and control supply inventories and chains in real time, reducing costs while improving environmental performance. In fast-food and organised retail, AI is being deployed directly against the problem of perishable-food waste: Reliance Retail has implemented AIenabled cameras spanning the journey from farm to store shelf to optimise produce handling and reduce food waste, alongside sustainability measures such as e-bike deliveries and solar-powered warehouses. Smaller, technology-native retail formats illustrate the same trend at a different scale: Daalchini, an Indian smart-vending start-up, is applying AI to reduce energy consumption and incorporate sustainability into its operations as it scales, and is exploring AI-powered smart logistics to minimise the carbon footprint of its distribution. Food manufacturing, processing, storage, and marketing using artificial intelligence - ScienceDirect +3

Despite this growing body of sector-specific evidence, most existing studies examine AI's role in isolated segments of the food value chain—agriculture, processing, or retail—rather than tracing its cumulative contribution to sustainability across the full farm-to-fork chain within a single national context. India offers a particularly instructive setting for such an integrated analysis, given its dual character as a large-scale agrarian economy and one of the world's fastest-growing digital and food-retail markets. This paper therefore examines the role of artificial intelligence in promoting sustainable supply chains across three interconnected segments of the Indian food industry—agriculture, manufacturing, and fast-food retail— with the aim of identifying common enablers, sector-specific applications, and the barriers that continue to constrain AIdriven sustainability outcomes. In doing so, the study seeks to contribute both to the academic literature on AI-enabled sustainable supply chain management and to practical policy and industry discourse on scaling these technologies responsibly across India's food ecosystem.

2.Research Objectives

The study is organised around five objectives:

1.To systematically review and classify AI applications across the full agricultural value chain, from production through to consumption (Lezoche et al., 2020).

2.To critically evaluate the technological innovations that are improving operational productivity, supplychain efficiency and direct consumer interaction (Klerkx et al., 2019).

3.To analyse how AI integration is reshaping industry business models and competitive dynamics (Brynjolfsson & McAfee, 2017).

4.To examine the ethical, socio-economic and governance challenges that accompany AI adoption — including algorithmic fairness, data protection and the risk of a widening digital divide (Ryan, 2020).

5.To propose practical guidelines and identify priority areas for future research that can support

equitable and sustainable AI adoption in the food sector (Tzachor et al., 2022).

3.Research Methodology

The study follows a mixed-methods design combining a systematic literature review, illustrative case studies and synthesis of secondary market data. Literature was identified through Scopus, Web of Science and Google Scholar for the period 2015–2022 using search terms such as "artificial intelligence in agriculture" and "machine learning food supply chain" (Mønster et al., 2021). After screening, more than 120 academic and industry sources were retained for analysis. This was supplemented by case studies of firms such as John Deere and IBM, and by market context drawn from McKinsey & Company (2020) and World Economic Forum reporting. The synthesised findings are organised into five thematic areas spanning the food value chain, summarised in Fig. 3.

Fig. 4 Systematic Literature Review Funnel

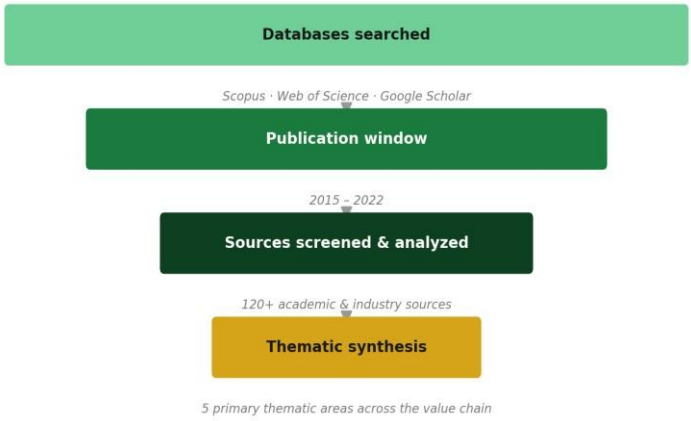

Fig. 4. Systematic Literature Review Funnel — Sources, Window and Thematic Output

Fig. 3 Five Thematic Pillars of AI Adoption Identified in the Reviewed Literature

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3.1AI in Agriculture and Food Production

a. Precision Agriculture

Precision agriculture combines AI, IoT sensors and remote sensing to support data-driven farm management. Machine-learning models that draw on multiple data sources have been reported to forecast yields and disease risk with accuracy above 85% (Liakos et al., 2018), while convolutional neural networks applied to plant imagery

have achieved classification accuracy above 90% in controlled studies of early plant-stress and disease detection (Mohanty et al., 2016). A widely cited commercial example is John Deere's See & Spray system, which uses real-time deep learning to apply herbicide only where needed, substantially cutting chemical use (John Deere, 2020).

b. Livestock and Aquaculture

In livestock farming, AI draws on data from wearable biosensors — tracking indicators such as activity level and body temperature — to support early disease detection and reproductive management (Neethirajan, 2020). In aquaculture, AI systems that monitor water-quality parameters and optimise feeding schedules have been shown to improve feed-conversion ratios by 10–15% in operational settings (Føre et al., 2018).

3.2AI in Food Manufacturing

Within manufacturing, AI is shifting operations away from manual, schedule-based processes toward predictive, automated and continuously optimised ones.

a. Predictive Maintenance

AI-based predictive maintenance uses sensor data and models such as recurrent neural networks to anticipate equipment failure before it occurs. This has been shown to cut unplanned downtime by up to 30% and extend the working life of equipment in food-processing settings (Zonta et al., 2020); Nestlé has reported meaningful reliability gains after adopting this approach (Nestlé, 2021).

b. Automated Quality Control

Deep-learning-based computer vision enables fast, consistent visual inspection for product defects. TOMRA's sorting systems, for example, combine hyperspectral imaging with neural networks to detect subtle imperfections, improving quality outcomes while reducing waste (TOMRA, 2021). c. Process Optimisation

Reinforcement-learning algorithms can adjust manufacturing parameters such as temperature and pressure in real time. Adaptive control of this kind has been associated with production-throughput gains of 10–20% alongside lower energy consumption (Kumar et al., 2021).

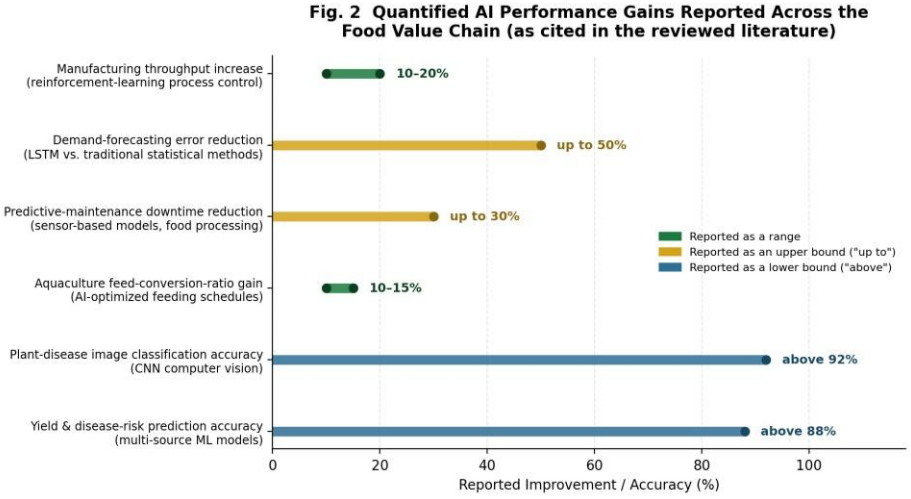

Fig. 2. Quantified AI Performance Gains Reported Across the Food Value Chain (synthesised from the reviewed literature)

3.3AI in Supply Chain Management

Food supply chains are especially difficult to manage because they combine product perishability, strict regulatory requirements and volatile demand. AI has introduced meaningful predictive and optimisation capability into this environment (Wang et al., 2018).

a. Demand Forecasting

Machine-learning approaches such as Long Short-Term Memory (LSTM) networks have outperformed traditional statistical forecasting methods, with Choi et al. (2018) reporting error-rate reductions of up to 50%. Walmart, for instance, uses AI models that combine weather data, historical sales and promotional calendars to sharpen demand forecasts for fresh produce (McKinsey & Company, 2020). b. Logistics Optimisation

AI algorithms can continuously recalculate optimal delivery routes using real-time inputs such as traffic

conditions, fuel costs and delivery windows. IBM's Watson Supply Chain platform, for example, uses AI to anticipate disruptions and recommend adaptive rerouting, helping maintain service continuity (IBM, 2020).

3.4AI in Consumer Engagement and Personalisation

AI is also reshaping how food businesses interact with consumers directly, enabling more personalised, datadriven experiences through mobile apps, wearable devices and digital health platforms — a response to growing consumer demand for customised nutrition and frictionless service (McKinsey & Company, 2020). This shows up in practice through personalised dietary recommendations based on individual biomarker and lifestyle data, and through conversational AI that automates customer service and strengthens engagement (Tzachor et al., 2022).

3.5Strategic Implications

AI adoption carries different implications for different stakeholders. Agricultural producers stand to gain higher yields and greater climate resilience, but adoption requires real investment in digital infrastructure and skills (Klerkx et al., 2019). Manufacturers gain operational efficiency and cost savings, provided they build internal data-analytics capability. Retailers — including fast-food chains — can use AI-driven personalisation to build customer loyalty, though this raises legitimate questions about how consumer data is used and regulated (Ryan, 2020). Policymakers, for their part, face the task of building governance frameworks that ensure algorithmic fairness, transparency and equitable access to these technologies (Desai, 2020).

3.6Challenges and Ethical Considerations

AI adoption in food systems is not without risk. Systems that process sensitive personal data raise genuine privacy concerns, and algorithmic decision-making can reproduce existing societal biases (Barocas et al., 2019). High adoption costs risk widening the digital divide between large and small operators, while the "black-box" nature of many advanced models limits explainability. Workforce displacement is a further concern, one that calls for proactive investment in reskilling and social support (Tzachor et al., 2022).

3.7Future Trends

Several developments are likely to shape the next phase of AI adoption in food systems: explainable AI (XAI) aimed at improving model transparency, edge computing to support decentralised real-time data processing, and generative AI applied to new product development. AI systems are also increasingly being designed to track sustainability metrics directly, such as carbon and water footprints (Lezoche et al., 2020). Realising this potential will depend on sustained collaboration between industry, academic researchers and regulators.

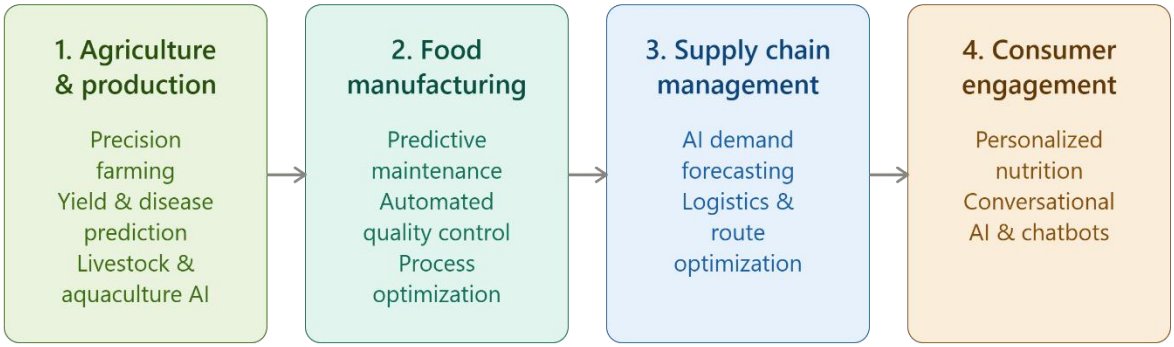

Fig. 1. AI Applications Across the Farm-to-Fork Food Value Chain, Mapped to Strategic Outcomes

This recreates the four-stage AI value chain from your figure:

1. **Agriculture & production** — precision farming, yield/disease prediction, livestock and aquaculture AI
2. **Food manufacturing** — predictive maintenance, automated quality control, process optimization
3. **Supply chain management** — AI demand forecasting, logistics and route optimization
4. **Consumer engagement** — personalized nutrition, conversational AI/chatbots

The strategic outcomes flow through the chain as: yield & climate resilience → operational efficiency & cost savings → service continuity → customer loyalty & trust — each stage's AI capability feeds the next, building from farm-level resilience up to stronger end-customer relationships.

4.Conclusion

Taken together, the evidence positions AI as a powerful tool for addressing food security, safety and sustainability challenges, with a demonstrated ability to raise productivity, cut waste and personalise nutrition at scale. Realising these benefits equitably, however, depends on establishing sound ethical guidelines, policies that promote inclusive access, and genuine cross-sectoral cooperation between industry, government and research institutions. Applied responsibly — including within consumer-facing segments such as India's fast-food industry — AI can help the food sector build a more resilient, efficient and sustainability-oriented supply chain for the future.

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