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Integrating AI in Sustainable Food and Health Systems: Bridging Nutrigenomics, Clinical Care, and Engineering

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ABSTRACT

Artificial Intelligence (AI) is rapidly transforming food systems by offering tools that improve productivity, safety, personalization, and resilience across the value chain. This review synthesizes current evidence on AI applications in agriculture, food processing, personalized nutrition, and supply chain management, and outlines governance and research priorities to ensure that technological gains translate into improved nutrition, equity, and sustainability. This study examined peer-reviewed literature and recent reports to map AI methods, use cases, benefits, and limitations. In agriculture, AI has enhanced precision farming, phenotyping and breeding, and post-harvest handling through sensor-based monitoring, predictive modeling, and automated decision support, leading to improved yields and produce quality. In food safety and processing, computer vision and machine learning have advanced contamination detection, quality grading and process optimization, reducing waste and improving consistency. In personalized nutrition, AI models integrate dietary records, phenotypic indicators and multiomic data to generate individualized recommendations and adaptive interventions that can improve metabolic outcomes and dietary adherence. For supply chain resilience, AI enabled forecasting, traceability and risk assessment support rapid response to disruptions and improve logistical efficiency. Despite demonstrable gains, widespread adoption faces challenges including variable data quality, algorithmic bias, limited transparency, infrastructure gaps, and potential environmental tradeoffs. Equity concerns emerge when resource constrained producers and consumers lack access to data, tools or skills. We propose a framework for responsible AI in food systems that emphasizes standards for data governance and model validation, inclusive design and capacity building, transparent reporting and life cycle assessment to evaluate environmental impacts. Policy levers, public private partnerships and cross disciplinary research are needed to harmonize technological innovation with nutritional and sustainability goals. Finally, we identify priority research areas including scalable validation studies, interoperable data platforms, methods to mitigate bias, and metrics to quantify nutritional and environmental co benefits. By integrating AI with sound governance and evidence based evaluation, the food sector can harness digital advances to support safe, nutritious and sustainable diets at scale. This review offers actionable recommendations for practitioners, researchers and policymakers to guide implementation, monitoring and evaluation of AI interventions that advance food security and public health and equity.

KEYWORDS

Artificial intelligence, food systems, food safety, precision agriculture, personalized nutrition, food manufacturing, supply chain resilience, sustainable diets, machine learning

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INTRODUCTION

Global food systems are confronting a confluence of challenges rising demand, nutritional inequities, and the imperative to reduce environmental impact, that require integrative technological and policy responses to achieve sustainable, health-promoting diets by 2030[1]. Artificial Intelligence (AI) has emerged as a transformative enabler across the food value chain, offering scalable tools to monitor safety, enhance productivity, and tailor nutrition strategies to individual and population needs[2]. In agriculture, AI-driven approaches including precision sensing, predictive modeling, and automated decision support are accelerating breeding, optimizing resource use, and improving the functional properties of produce, thereby strengthening both productivity and nutritional quality[3].

Within food industry operations, AI innovations are expanding from quality control and contamination detection to process optimization and product innovation, enabling faster, more reliable manufacturing and responsive product development pipelines[4]. At the intersection of manufacturing and consumer health, AI supports personalized nutrition by integrating multi-omic data, dietary intake, and lifestyle measures to generate individualized recommendations and adaptive interventions that can improve metabolic outcomes and adherence to healthier diets[5]. Beyond the farm and factory, the resilience of food supply chains is increasingly bolstered by AI-enabled analytics that enhance demand forecasting, traceability, and organizational responsiveness, helping firms anticipate disruptions and maintain continuity under dynamic conditions[6].

Despite its promise, responsible deployment of AI in food and nutrition requires careful attention to data quality, transparency, equity and environmental trade-offs so that technological gains translate into meaningful public-health and sustainability outcomes. This manuscript synthesizes current evidence on AI applications across agriculture, food processing, personalized nutrition and supply-chain resilience, and it outlines a framework for integrating technological innovation with nutritional science and policy to advance sustainable, equitable food systems. The aim is to provide practitioners, researchers, and policymakers with a coherent assessment of where AI is delivering impact today and the priorities for research and governance needed to ensure AI strengthens food security, safety and nutritional well-being at scale.

AI IN NUTRIGENOMICS FOR SUSTAINABLE FOOD SYSTEMS

AI-driven genomic data analysis for personalized nutrition: The AI-driven analytic frameworks are enabling the interpretation of large-scale genomic datasets to inform personalized dietary recommendations. By integrating SNP profiles, clinical biomarkers, microbiome measures, and lifestyle metadata, modern machine-learning (ML) pipelines detect complex, nonlinear associations between genotype and nutrient metabolism, thereby enabling tailored dietary strategies for disease prevention and health promotion[7,8].

In practice, supervised learning models (e.g., random forests, gradient-boosted trees) and ensemble methods are applied to genotype phenotype cohorts to rank polymorphisms by effect size on metabolic endpoints; deep networks and representation learning then extract latent patterns that link variant combinations to nutrient-response phenotypes[7,8].

- **Machine learning for SNP interpretation:** The ML approaches improve on classical association testing by capturing epistatic and non-additive effects among SNPs, enabling detection of combinatorial genetic signatures relevant to micronutrient handling and drug nutrient interactions. Models trained on multi-cohort datasets can prioritize SNPs that influence absorption, transport, or enzymatic conversion of vitamins and minerals; these prioritized variants become inputs for downstream predictive rules in clinical decision support[7,8]

- **Predictive models for diet gene interactions:** Integrative predictive models combine genotype with meal composition and temporal glucose, lipid, or metabolite readouts to forecast individual metabolic responses (e.g., postprandial glycemia, lipid excursion). Such models have shown predictive value for tailoring meal plans, optimizing macronutrient distribution, and informing supplementation strategies that account for genetic predisposition[7,8]

Figure 1 illustrates the sequential stages of the AI-driven nutrigenomic analysis pipeline described. It highlights how raw genomic and lifestyle data are collected, preprocessed, and analyzed through machine learning models. The workflow demonstrates the integration of AI to generate personalized nutrition insights from complex genotype phenotype interactions.

AI in food composition and nutrient profiling: Computer vision and deep learning have matured to the point that automated food recognition and nutrient estimation from images are viable at scale. Convolutional Neural Networks (CNNs), vision transformers, and hybrid ensembles can identify dishes, segment plates, and estimate portion sizes, feeding into nutrient-estimation modules that map visual features to macronutrient and, where available, micronutrient content[9,10].

Deep learning for food image recognition and nutrient estimation: Training on large, annotated datasets underpins accurate recognition and portion estimation; transfer learning and multimodal models (image+textual metadata) further improve robustness in real-world settings. The DL-enabled pipelines reduce logging burden for users and clinicians by automating dietary intake capture and generating nutrient summaries suitable for integration with genomic risk scores[9,10].

Databases and ontologies for nutrient-gene mapping: The AI-driven nutrigenomics depends on structured knowledge linking food items and nutrient components to gene expression or metabolic pathways. Curated nutrigenomic resources and ontologies standardize descriptors (food taxa, nutrient forms, gene targets), enabling consistent mapping from foods identified by image or self-report to gene-level effects used by predictive models[9,10].

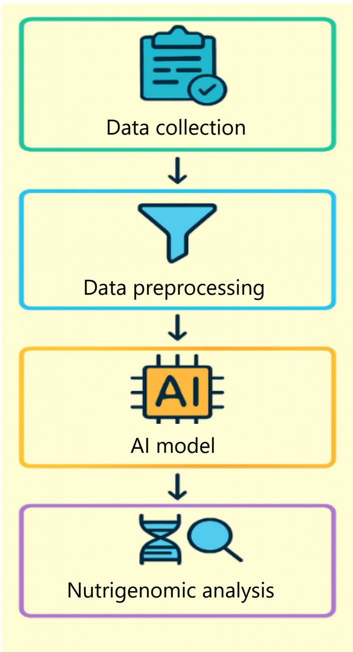

Fig. 1: Workflow diagram of AI-based nutrigenomic analysis pipeline (self-generated)
The diagram depicts a four-step workflow beginning with data collection, followed by preprocessing, AI model application, and nutrigenomic analysis, Each stage is represented by a distinct icon and color-coded box connected by arrows and The flowchart visually summarizes the transformation of raw data into actionable nutrition outcomes

Table 1: Comparative AI tools and databases for nutrient profiling

Tool/Database	Primary function	Notes/Applications	Citation(s)
Food image recognition (DL)	Identify foods; estimate portion and nutrients	CNNs/transformer-based systems for automated meal logging	Liu *et al.*[9]
USDA food data Central	Authoritative nutrient composition	Core nutrient reference for downstream mapping	Liu *et al.*[9] and Ford *et al.*[10]
FooDB	Food metabolite and bioactive compound database	Supports nutrient–gene and metabolite pathway mapping	Liu *et al.*[9]
NutrigenomeDB/Eat4Genes	Curated nutrient→gene expression relations	Databank of experimental nutrigenomic links for models	Ford *et al.*[10]
FoodOn ontology	Standardised food descriptors	Facilitates cross-dataset integration and semantic mapping	Liu *et al.*[9] and Ford *et al.*[10]

Table lists tool/database name, primary function, practical notes and citation to help compare image-recognition and nutrigenomic resources. Entries include deep-learning food-image systems, USDA FoodData Central, FooDB, NutrigenomeDB/Eat4Genes and FoodOn ontology, Abbreviations: AI: Artificial intelligence, DL: Deep learning, CNN: Convolutional neural network, USDA: U.S. Department of Agriculture and DB: Database

Table 1 summarizes core AI tools, image-recognition systems, and curated food/nutrient databases used for automated nutrient profiling and nutrigenomic mapping. It highlights primary functions and practical applications (e.g., portion estimation, ontology mapping) that support image→nutrient pipelines. Use of these resources underpins the section's discussion of computer-vision and ontology-driven nutrient gene mapping.

AI for crop biofortification and functional food design: The AI accelerates breeding and metabolic design workflows that produce nutrient-dense crops and novel functional foods. The AI-driven genomic selection models and ML-augmented metabolic engineering reduce cycle times and increase the precision of trait introgression, enabling scalable biofortification programs[11,12].

- **Genomic selection in plant breeding:** Deep learning models trained on genotype × phenotype panels improve prediction accuracy for complex, quantitative nutrient traits relative to conventional genomic-estimation methods. By more accurately predicting breeding value for micronutrient content, AI enables breeders to select superior parental combinations earlier in breeding cycles, shortening timelines to release biofortified cultivars[11,12]
- **AI-assisted metabolic engineering for nutrient-rich crops:** Within metabolic engineering, ML tools analyze enzyme kinetics, pathway topology, and gene regulatory networks to nominate edits or transgenes that reroute flux toward desired micronutrients (e.g., provitamin A, folate, iron chelators). AI-guided pathway design reduces experimental iterations, enabling more efficient construction of crops or microbial platforms for functional-ingredient production[11,12]

Figure 2 illustrates the AI-assisted biofortification workflow described in of the manuscript, showing how genomic selection feeds into AI-driven analysis that guides metabolic engineering to produce nutrient-rich crops.

It emphasizes the two principal approaches discussed in genomic selection in plant breeding and AI-assisted metabolic engineering and the sequential decisions that shorten breeding cycles and optimize nutrient pathways.

Arrows indicate data and action flow from genotype-informed selection through AI interpretation to laboratory pathway edits and, ultimately, field-ready biofortified cultivars.

Sustainability metrics in AI-driven food systems: The AI applications increasingly connect nutrigenomic and crop-design interventions with environmental assessments, enabling systems-level optimization that balances nutritional goals with planetary constraints[13,14].

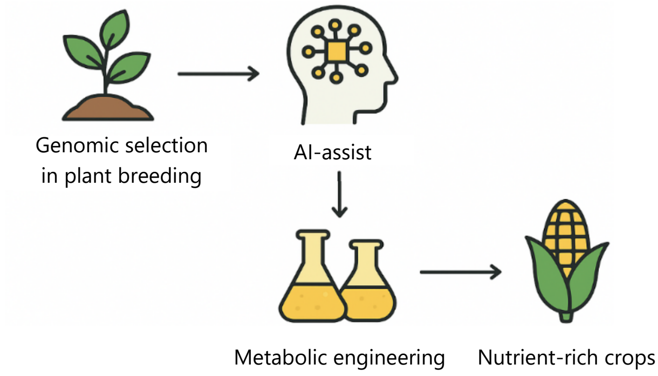

Fig. 2: AI-assisted biofortification process flow (self-generated)
Left-to-right and top-to-bottom icons represent: genomic selection (seedling/soil), AI analysis (head with network), metabolic engineering (laboratory flasks), and nutrient-rich crops (ear of corn), Black arrows between icons denote the directional workflow; concise labels beneath each icon identify the stage and Simplified icons and a restrained color palette improve legibility for both print and presentation formats

Table 2: AI applications for reducing carbon and water footprints

AI application	Domain	Potential impact/Mechanism	Citation(s)
AI-enhanced LCA optimization	Supply-chain analysis	Identifies supply-chain levers that can reduce GHG emissions (~46%)	Nikkhah *et al.*[13]
Water-footprint prediction (ML)	Crop water management	High-accuracy water-use estimation enabling targeted conservation	Nikkhah *et al.*[13]
Precision irrigation (AI control)	Field irrigation	Schedules irrigation using real-time data to reduce water use	Nikkhah *et al.*[13] and Emeç *et al.*[14]
Precision fertilization (ML-guided)	Nutrient management	Reduces excess fertilizer application and N_2O emissions	Emeç *et al.*[14]

Maps AI applications to sustainability domains with short notes on mechanisms and expected impacts. Rows include AI-enhanced LCA optimization, water-footprint prediction, precision irrigation and ML-guided fertilization, Abbreviations: ML: Machine learning, LCA: Life cycle assessment and AI: Artificial intelligence

Life cycle assessment (LCA) integration with AI: Hybrid frameworks that combine LCA inventories with machine-learning optimization enable rapid scenario evaluation and highlight interventions (input substitution, process redesign, logistics optimization) that yield the largest reductions in greenhouse gas emissions or resource use. These hybrid approaches make LCA outputs actionable by automatically recommending operational changes informed by predictive models[13,14].

Predictive models for environmental footprint reduction: High-resolution ML models estimate crop water and carbon footprints at farm and regional scales, enabling precision interventions (irrigation scheduling, input matching) that reduce resource consumption without sacrificing yield. Predictive ensembles trained on climatic, soil, and management data have demonstrated high fidelity in water-footprint estimation and provide decision inputs for water- and carbon-saving strategies[13,14].

Table 2 maps AI methods to sustainability applications discussed in showing how ML and hybrid LCA approaches reduce environmental impacts. It links specific AI applications (e.g., precision irrigation, LCA optimization) to their domain and expected mechanism of impact. The table supports the section's argument that AI can make environmental trade-offs actionable.

AI IN CLINICAL CARE FOR NUTRITION AND HEALTH

AI-powered clinical decision support for nutrition therapy: The integration of Electronic Health Records (EHRs) with nutrigenomic data has emerged as a transformative approach in clinical nutrition. By combining genomic profiles with longitudinal health data, AI-driven Clinical Decision Support Systems (CDSS) can generate personalized dietary recommendations that account for genetic predispositions to conditions such as type 2 diabetes, obesity, and cardiovascular disease[15].

Table 3: AI-enabled clinical nutrition decision support systems

Component of system	Description	Example applications	Citation(s)
Data ingestion layer	Integration of EHR, nutrigenomic, and lifestyle data	Collects patient history, genetic markers, and dietary logs	Saseedharan and Lewis[15] and Varayil *et al.*[16]
AI analytics engine	Predictive modeling, NLP, reinforcement learning	Forecasts malnutrition, nutrient deficiencies, and disease risk	Varayil *et al.*[16] and Bharmal[17]
Decision support interface	Clinician dashboards and patient-facing apps	Provides personalized nutrition recommendations	Bharmal[17]
Feedback loop	Continuous learning from patient outcomes	Refines dietary interventions dynamically	Varayil *et al.*[16]
Clinical utility	Reduces clinician workload, improves patient adherence	Enhances precision nutrition therapy	Saseedharan and Lewis[15] and Varayil *et al.*[16] and Bharmal[17]

Breaks down system components (data ingestion, analytics engine, interface, feedback loop) with descriptions and example applications. Shows how EHR, nutrigenomic, wearable, and lifestyle inputs feed an AI analytics engine and clinician/patient interfaces, Abbreviations: HER: Electronic health record, CDSS: Clinical decision support system, NLP: Natural language processing and AI: Artificial Intelligence

Machine learning algorithms embedded in EHR platforms can identify nutrient gene interactions, enabling clinicians to tailor interventions at the molecular level[16].

Predictive analytics further enhances diet-related disease management by leveraging large-scale datasets to forecast patient outcomes. For example, deep learning models trained on EHR and nutrigenomic data can predict the likelihood of malnutrition, sarcopenia, or micronutrient deficiencies before clinical symptoms manifest[17].

These systems also support real-time monitoring of dietary adherence, integrating wearable data streams with clinical records to refine recommendations dynamically.

The architecture of an AI-enabled clinical nutrition decision support system typically includes:

- **Data ingestion layer:** EHR, nutrigenomic, and lifestyle data
- **AI analytics engine:** predictive modeling, natural language processing (NLP), and reinforcement learning
- **Decision support interface:** clinician dashboards and patient-facing mobile apps
- **Feedback loop:** continuous learning from patient outcomes to refine algorithms

Such systems have demonstrated improved accuracy in predicting diet-related complications, reduced clinician workload, and enhanced patient engagement in nutrition therapy[15-17].

Table 3 breaks down components of AI-powered clinical decision support described in (data ingestion, analytics engine, interfaces, feedback loop). It pairs each component with a concise description and example application to show how nutrigenomic data are operationalized in clinical workflows. The Table 3 clarifies the system architecture that underlies clinical personalization claims.

AI in metabolic health monitoring: The rise of wearable sensors and continuous glucose monitoring (CGM) devices has revolutionized metabolic health tracking. The AI algorithms process the vast streams of real-time data from CGMs, accelerometers, and smartwatches to detect subtle physiological changes indicative of metabolic dysregulation[18].

For instance, Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) have been applied to CGM data to predict postprandial glucose excursions, enabling proactive dietary adjustments[19].

Table 4: AI-based metabolic health monitoring devices and algorithms

Device/Algorithm	Data source	AI technique	Clinical application	Citation(s)
Guardian connect (Medtronic)	Continuous glucose monitoring (CGM)	Predictive ML models	Alerts for hypoglycemia/ hyperglycemia	Choubey *et al.*[18]
Dexcom G7	CGM+cloud integration	Deep learning forglycemic variability	Personalized glucose trend prediction	Anwar *et al.*[19]
Smartwatches (Fitbit, apple watch)	Heart rate, sleep, activity	Random forest, CNNs	Early detection of metabolic syndrome	Choubey *et al.*[18]
RNN-based CGM analysis	CGM time-series data	Recurrent neural networks	Predicts postprandial glucose excursions	Anwar *et al.*[19]
Gradient boosting models	Multimodal health data	Ensemble learning	Stratifies metabolic syndrome risk	Choubey *et al.*[18] and Anwar *et al.*[19]

Catalogs representative devices/algorithms, their data sources and the AI techniques used for metabolic monitoring. Examples include CGM systems (Dexcom/Gardian), smartwatches, RNN-based time-series analyses and ensemble models, Abbreviations: CGM: Continuous glucose monitoring, RNN: Recurrent neural network, CNN: Convolutional neural network and AI: Artificial intelligence

These models outperform traditional regression-based approaches by capturing nonlinear dynamics in glucose variability.

AI also plays a pivotal role in the early detection of metabolic syndrome (MetS). By integrating multimodal data, such as blood pressure, lipid profiles, and anthropometric measures, machine learning classifiers can identify individuals at high risk of MetS before clinical diagnosis[18].

Random forest and gradient boosting models have shown particular promise in stratifying risk across diverse populations.

Table 4 catalogs representative devices and algorithm classes discussed in linking data sources (e.g., CGM, smartwatches) to AI techniques and clinical uses. It provides concrete examples (products and model types) to illustrate the section's points about real-time metabolic monitoring and prediction. The table supports comparisons of technique, data input, and clinical application.

AI for personalized dietary interventions in chronic disease: The AI-driven personalization of dietary interventions has gained traction in managing chronic diseases such as diabetes, cardiovascular disease, and obesity[20].

Case studies demonstrate that AI-generated diet plans, informed by biomarkers and lifestyle data, can significantly improve glycemic control, lipid profiles, and weight management outcomes[21].

For diabetes, reinforcement learning algorithms have been applied to adapt dietary recommendations in real time, adjusting macronutrient composition based on continuous glucose monitoring feedback[20,21].

In cardiovascular disease, AI models integrate dietary intake with imaging and biomarker data to optimize heart-healthy diets, such as the DASH or Mediterranean diet[21].

Obesity management has benefited from AI-driven behavioral nudges delivered via mobile apps, which personalize caloric targets and meal timing strategies.

The flowchart of AI-driven adaptive dietary intervention typically includes:

- **Data collection:** Biomarkers, wearable data, patient-reported outcomes
- **AI processing:** Reinforcement learning and predictive modeling
- **Personalized intervention:** Adaptive meal plans and behavioral prompts
- **Outcome monitoring:** Continuous feedback loop for refinement

Table 5: AI-driven personalized dietary interventions in chronic disease

Chronic disease	AI approach	Intervention strategy	Clinical outcome	Citation(s)
Diabetes	Reinforcement learning with CGM feedback	Adaptive macronutrient adjustments	Improved glycemic control	Wang *et al.*[20]
Cardiovascular disease	Predictive modeling with biomarkers and imaging	Optimized DASH/ Mediterranean diet plans	Reduced CVD risk markers	Wang *et al.*[20]
Obesity	AI-driven behavioral nudges via mobile apps	Personalized caloric targets and meal timing	Enhanced weight loss adherence	Wang *et al.*[20]
Multi-disease management	Hybrid AI models integrating lifestyle+ biomarkers	Adaptive diet plans across comorbidities	Improved long-term adherence	Gavai and van Hillegersberg[21]
Patient engagement	Conversational AI and mobile coaching	Real-time feedback and motivation	Higher adherence rates	Gavai and van Hillegersberg[21]

Pairs chronic conditions with AI approaches, intervention strategies and reported clinical outcomes. Rows include diabetes (reinforcement-learning with CGM feedback), CVD (predictive modeling+biomarkers) and obesity (behavioral nudges via apps), Abbreviations: RL: Reinforcement learning, CVD: Cardiovascular disease, CGM: Continuous glucose monitoring and AI: Artificial intelligence

These adaptive systems have demonstrated superior adherence rates compared to static diet plans, highlighting the potential of AI to transform chronic disease management[20,21].

Table 5 summarizes AI approaches for chronic-disease dietary management covered in pairing diseases (diabetes, CVD, obesity) with algorithmic strategies and measured outcomes. It clarifies which AI methods (e.g., reinforcement learning, predictive modeling) map to which intervention strategies and clinical endpoints. The table condenses case-study evidence supporting adaptive, AI-tailored diets.

AI in public health nutrition surveillance: At the population level, AI has become indispensable in nutrition surveillance. Machine learning models analyze dietary intake data from national surveys, retail purchase records, and social media to identify emerging dietary patterns[22].

For example, natural language processing applied to food diaries and online discussions can reveal shifts in consumption trends, such as increased plant-based diets or ultra-processed food intake[23].

Predictive modeling has also been employed to forecast malnutrition and obesity trends. By integrating socioeconomic, environmental, and dietary data, AI systems can predict hotspots of undernutrition or obesity, guiding targeted public health interventions[24].

These models have been used to simulate the impact of policy measures, such as sugar taxes or food subsidy programs, on population dietary behaviors.

Table 6 lists model classes and primary data sources used for population-level nutrition surveillance as discussed in alongside intended public-health impacts. It showcases how NLP, deep learning, Bayesian networks and random-forest models are applied to surveys, satellite imagery and social media. The table highlights surveillance use-cases and the policy-relevant outputs each model class can generate.

ENGINEERING INNOVATIONS FOR AI-ENABLED FOOD AND HEALTH SYSTEMS

Smart food production systems: The integration of IoT-enabled precision agriculture with AI has transformed farming into a data-driven enterprise. Smart sensors now monitor soil moisture, nutrient levels, and microclimatic conditions in real time, enabling farmers to optimize irrigation, fertilization, and pest control strategies[25].

The AI algorithms process these heterogeneous data streams to generate predictive models that guide planting schedules, crop rotation, and yield forecasting[26].

Table 6: AI models in public health nutrition surveillance

AI model	Data source	Application	Public health impact	Citation(s)
Random forest models	National dietary surveys	Predict obesity prevalence	Guides obesity prevention programs	An and Wang[22]
Deep learning models	Satellite imagery of food environments	Identifies food deserts and obesogenic areas	Supports urban planning and food policy	Ferreira *et al.*[23]
Bayesian networks	Socioeconomic+dietary data	Forecasts malnutrition risk	Targets vulnerable populations	Ferreira *et al.*[23] and Mendes *et al.*[24]
NLP-based models	Food diaries, social media	Detects emerging dietary trends	Monitors shifts in population diet	Ferreira *et al.*[23] and Mendes *et al.*[24]
Predictive policy simulations	Integrated socioeconomic+ nutrition datasets	Models impact of sugar taxes, subsidies	Informs national nutrition policy	Mendes *et al.*[24]

Lists AI model classes, primary data sources, applications and the public-health impacts they generate. Includes random-forest models on national surveys, deep learning on satellite imagery, Bayesian networks on socioeconomic+diet data, and NLP on diaries/social media, Abbreviations: RF: Random forest, DL: Deep learning, BN: Bayesian network, NLP: Natural language processing and ML: Machine learning

Table 7: Smart food production systems

Technology	Application	Benefits	Citation(s)
IoT soil sensors	Monitor soil moisture, nutrients	Precision irrigation and fertilization	Miller *et al.*[25]
AI crop models	Predict yield, detect stress	Optimized planting and harvesting	Miller *et al.*[25] and Chaurasiya *et al.*[26]
Vertical farming AI	Climate and nutrient control	Year-round production, reduced water use	Chaurasiya *et al.*[26]
Robotics in farming	Automated seeding, harvesting	Reduced labor costs, higher efficiency	Chaurasiya *et al.*[26] and Oh and Lu[27]
Cloud-based platforms	Remote monitoring and analytics	Scalable smart farm management	Oh and Lu[27]

Itemizes smart-farm technologies, their specific applications and the main productivity/sustainability benefits. Entries include IoT soil sensors, AI crop models, vertical/controlled-environment farming systems, robotics and cloud platforms, Abbreviations: IoT: Internet of things, AI: Artificial Intelligence; CEA: Controlled-environment agriculture and SW/HW: Software/hardware (where applicable)

Vertical farming and controlled environment agriculture (CEA) represent another frontier. By leveraging AI-driven climate control systems, vertical farms can regulate light spectra, CO_2 concentration, and nutrient delivery to maximize crop productivity[27].

These systems reduce water consumption by up to 90% compared to traditional agriculture, while minimizing pesticide use and ensuring year-round production.

The smart farm architecture integrates IoT sensors, robotics, and AI analytics into a closed-loop system:

- IoT sensors capture soil, plant, and environmental data
- The AI analytics optimize resource allocation and predict crop stress
- Robotics automate seeding, harvesting, and crop monitoring
- Cloud platforms enable remote decision-making and scalability

This convergence enhances sustainability, reduces labor dependency, and improves resilience against climate variability[25-27].

Table 7 itemizes smart-farm technologies described in matching each technology (IoT soil sensors, AI crop models, vertical-farm AI, robotics, cloud platforms) with applications and primary benefits. It provides a quick reference that connects specific engineering tools to sustainability and productivity outcomes. The table supports the section’s claims about closed-loop farm optimization.

Table 8: AI applications in food safety and quality control

AI Application	Technology	Use case	Benefits	Citation(s)
Contamination detection	Computer vision+ CNNs	Identify microbial/foreign objects	Real-time safety assurance	Dhal and Kar[28]
Shelf-life prediction	Machine learning regression	Predict spoilage timelines	Reduced food waste	Dhal and Kar[28]
Predictive maintenance	Sensor data+ML models	Anticipate equipment failure	Reduced downtime, safer production	Dhal and Kar[28] and Song *et al.*[29]
Automated quality control	Vision+NLP	Detect texture, color, defects	Consistency in food quality	Song *et al.*[29]
Risk modeling	AI+IoT integration	Hazard analysis	Proactive safety management	Song *et al.*[29]

Summarizes AI use-cases in processing and safety, listing technologies, use-cases and operational benefits (e.g., real-time contamination detection, shelf-life prediction). Rows cover computer-vision contamination detection, ML shelf-life regression, predictive maintenance from sensor data and automated quality control, Abbreviations: CNN: Convolutional neural network, ML: Machine learning, IoT: Internet of Things, AI: Artificial intelligence and NLP: Natural language processing

AI in food processing and safety engineering: Food safety remains a global challenge, with contamination incidents causing significant health and economic burdens. Computer vision systems powered by deep learning are increasingly deployed in food processing plants to detect microbial contamination, foreign objects, and quality defects[28].

These systems outperform manual inspection by providing real-time, high-resolution analysis of food products on production lines.

Predictive maintenance is another critical application. The AI models analyze sensor data from machinery, such as vibration, temperature, and acoustic signals, to predict equipment failures before they occur[29].

This reduces downtime, prevents contamination risks from malfunctioning equipment, and lowers operational costs.

Together, these innovations enhance food safety, improve quality assurance, and strengthen consumer trust[28,29].

Table 8 summarizes AI use-cases in processing and safety discussed in pairing each AI application (contamination detection, shelf-life prediction, predictive maintenance) with the enabling technology and the operational benefit. It clarifies how real-time vision and sensor analytics reduce risks and downtime. The table acts as a concise inventory for food-safety engineering interventions.

AI-driven supply chain optimization for sustainable food distribution: The food supply chain faces challenges of demand variability, waste, and traceability. AI-driven demand forecasting models use historical sales, weather data, and consumer behavior to predict demand with high accuracy[30].

This reduces overproduction, minimizes waste, and ensures timely distribution.

Blockchain integration enhances traceability by creating immutable records of food movement across the supply chain[31].

When combined with AI, blockchain enables real-time fraud detection, contamination source tracing, and compliance monitoring[32].

Table 9: AI in sustainable food supply chain optimization

Application	AI/Tech used	Benefits	Citation(s)
Demand forecasting	ML, deep learning	Reduced waste, accurate planning	Chen *et al.*[30]
Route optimization	AI logistics models	Lower emissions, faster delivery	Chen *et al.*[30]
Blockchain traceability	Blockchain+AI	Fraud prevention, transparency	Zhu *et al.*[31]
Inventory optimization	Predictive analytics	Reduced spoilage, cost savings	Qian *et al.*[32]
Sustainability tracking	AI+IoT	Carbon footprint monitoring	Qian *et al.*[32]

Lists supply-chain applications (demand forecasting, route optimization, blockchain traceability, inventory and sustainability tracking) with AI/tech and benefits. Shows how ML/AI forecasts and blockchain-ledgers combine with IoT to reduce waste, lower emissions and improve traceability, Abbreviations: ML: Machine learning, AI: Artificial intelligence, IoT: Internet of things and BC: Blockchain

The AI-enabled sustainable food supply chain model includes:

- **Data collection:** IoT sensors, retail data, logistics
- **The AI forecasting:** Demand prediction, route optimization
- **Blockchain ledger:** Transparent traceability
- **Sustainability metrics:** Carbon footprint, waste reduction

This integration improves efficiency, reduces environmental impact, and strengthens consumer confidence[30-32].

Table 9 lists supply-chain applications (demand forecasting, route optimization, blockchain traceability, inventory optimization, sustainability tracking) discussed and the AI/tech used for each. It links each application to its operational benefit (waste reduction, lower emissions, fraud prevention). The table synthesizes the section's proposed model for AI+blockchain-enabled sustainable distribution.

Human-AI collaboration in food and health engineering: The success of AI in food and health systems depends on human AI collaboration. The Co-design approaches involving nutritionists, clinicians, and engineers ensure that AI tools are user-centered, clinically relevant, and ethically aligned[33].

Collaborative design workshops have shown that involving domain experts improves algorithm interpretability and adoption.

Ethical and regulatory considerations are equally critical. Issues such as data privacy, algorithmic bias, and accountability must be addressed to ensure trust in AI systems[34].

Regulatory frameworks are emerging to guide responsible AI deployment in food and health engineering, emphasizing transparency, fairness, and human oversight[35].

This collaboration ensures that AI augments rather than replaces human expertise, fostering innovation while safeguarding ethical standards[33-35].

Table 10 maps ethical principles (transparency, fairness, accountability, privacy, human-centric design) described in to concrete frameworks/guidelines and their application in food-health AI systems. It clarifies governance levers and recommended practices for trustworthy deployment. The table supports the section's emphasis on co-design and regulatory alignment.

RECOMMENDATION AND FUTURE PERSPECTIVES

Artificial intelligence holds real promise for nutrigenomics, food engineering and clinical nutrition, but realizing that promise requires practical, people centered action. We recommend three mutually reinforcing priorities. First, strengthen data governance and adopt open, interoperable ontologies so that datasets can be combined responsibly and traced back to their origin. Second, commit to prospective,

Table 10: Ethical frameworks and guidelines for ai in food-health systems

Ethical principle	Framework/Guideline	Application in food-Health AI	Citation(s)
Transparency	EU AI Act, FDA guidelines	Explainable AI in nutrition tools	Jumper *et al.*[33]
Fairness	IEEE Ethically Aligned Design	Avoid bias in dietary algorithms	Payili[34]
Accountability	WHO digital health ethics	Human oversight in AI decisions	Agrawal *et al.*[35]
Privacy and security	GDPR, HIPAA	Protect patient and consumer data	Jumper *et al.*[33] and Payili[34]
Human-centric design	Co-design methodologies	Collaboration with clinicians/nutritionists	Agrawal *et al.*[35]

Maps ethical principles to concrete frameworks/guidelines and their application in food-health AI deployments. Entries include transparency (EU AI Act/FDA guidance), fairness (IEEE EAD), accountability (WHO digital health ethics), and privacy (GDPR/HIPAA), Abbreviations: EU AI Act: European union AI act, FDA: U.S. Food and drug administration, WHO: World health organization, GDPR: General data protection regulation, HIPAA: Health insurance portability and accountability Act, IEEE EAD: IEEE ethically aligned design and AI: Artificial intelligence

multi site model validation using diverse cohorts and realistic field data to make sure tools work beyond the lab. Third, embed human centered design from the start so that equity, explainability and usability guide both research and deployment. These foundational steps will reduce bias, build clinician and public trust, and accelerate safe translation into practice[36-38].

On the research and engineering side, we urge focused investment in longitudinal, multi cohort clinical studies that connect genomic, microbiome, clinical and behavior data to clear health outcomes. Build modular, interoperable platforms that enable federated learning and privacy preserving analytics so institutions can collaborate without exposing sensitive data. Pair AI model development with life cycle assessment and supply chain impact evaluation so nutritional gains do not come at the expense of planetary health. Equip biochemists, nutritionists and engineers with applied AI literacy and support cross discipline teams that can translate algorithmic insights into safe laboratory and clinical practice. These measures reflect and extend recent work on integrating AI into biomolecular research[39].

Practical implementation also needs supportive policy, funding and governance. Funders should create targeted streams for implementation research in low resource settings and for independent validation studies. Regulators, industry and civil society should require transparent model documentation, versioned audit trails and accessible model cards so decisions informed by AI are auditable and explainable. Convene multi stakeholder governance fora that include researchers, clinicians, community representatives and industry to steward deployment and to align incentives with public health and sustainability[39].

Finally, promote open science as the default. Shared, well curated datasets and reproducible pipelines accelerate progress and reduce duplication. Incentivize reproducible code release, curated benchmark datasets and registered reports so that findings are verifiable and translatable. Encourage partnerships that pair technological innovation with implementation science so that promising tools mature into usable, safe interventions. These recommendations align with recent analyses on AI integration in biochemistry and biomedical sciences[39,40]. By centering ethics, transparency and collaboration we can move from individual proofs of concept to durable improvements in nutrition and health[39,40].

CONCLUSION

Based on the integrated review and analyses presented in this manuscript, AI-enabled nutrigenomics and engineering innovations demonstrate strong potential to personalize nutrition and advance sustainable food systems. Machine-learning frameworks for genomic interpretation, computer-vision nutrient profiling, and AI-assisted biofortification collectively offer scalable routes to improve nutrient outcomes while lowering environmental footprints. Clinical deployment of AI-via EHR-integrated decision support, CGM-informed adaptive diets, and wearable-enabled monitoring can enhance prevention and management of diet-related disease when validated in diverse populations. Engineering advances (IoT-driven precision agriculture, vertical farming, and AI-optimized logistics with blockchain traceability) provide actionable mechanisms to reduce waste, water use, and emissions across supply chains. Robust validation, data interoperability, and transparent governance are prerequisites for safe, equitable adoption; attention to algorithmic bias, privacy and regulatory compliance must guide implementation. Overall, the manuscript outlines a pragmatic agenda that balances technological innovation with ethical, regulatory and socioecological safeguards to realize AI-driven nutrition and food systems at scale.

SIGNIFICANCE STATEMENT

This manuscript synthesizes advances in AI applications across nutrigenomics, crop biofortification, food processing, supply chain engineering and clinical nutrition, highlighting integrated pathways to improve nutrition and sustainability. It shows how machine learning, computer vision and metabolic engineering can accelerate development of nutrient rich crops and enable precision dietary interventions. The review underscores systems level integration with life cycle assessment and supply chain analytics to align nutritional objectives with environmental constraints. Ethical governance, data interoperability and rigorous validation are identified as prerequisites for equitable, safe and transparent deployment. Priority future actions include longitudinal multi cohort studies, standardized ontologies and open data practices to strengthen model generalizability and reproducibility. By combining technical, policy and codesign perspectives, the manuscript offers a pragmatic roadmap for translating AI enabled innovations into scalable, equitable food and health solutions.

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