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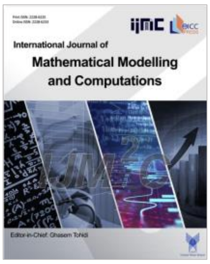

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Design and Implementation of Multi -Criterion Decision Systems Based on Artificial Intelligence in Optimizing Production Process in Food and Drinks Industries

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Abstract

This study introduces an innovative, multi-layered artificial intelligence (AI) framework designed to optimize food and beverage production processes, with an emphasis on sustainability, safety, and operational efficiency. The framework integrates hierarchical fuzzy analytic hierarchy process (fuzzy AHP) for multi-criteria decision-making, advanced data preprocessing techniques including auto encoders and feature engineering, and diverse AI models such as deep reinforcement learning (DRL), convolutional neural networks (CNN), and gradient boosting machines (GBM). A comprehensive digital twin environment simulates real-time plant operations, enabling validation and scenario analysis. The proposed methodology employs a ten-round decision refinement process, incorporating expert judgment, sensor data, visual defect detection, and predictive analytics to dynamically control process parameters, quality assurance, and resource allocation. The case study conducted within a Tehran dairy processing plant demonstrates substantial improvements in operational metrics: a reduction of energy consumption by 8%, microbial counts by 15%, waste by 10%, and zero safety violations over a three-month period. The integration of explainable AI (XAI) techniques enhances interpretability and stakeholder trust. The findings underscore the potential of such integrated AI-driven systems to revolutionize Industry 4.0 practices in food manufacturing offering pathways toward smarter, safer, and more sustainable production paradigms. This research provides a scalable, adaptable blueprint for future deployment across diverse industrial contexts.

Keywords: Design and Implementation; Multi -Criterion Decision System; Artificial Intelligence; Optimizing; Production Process; Food and Drinks Industries

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1. Introduction

The proliferation of artificial intelligence (AI) technologies has profoundly transformed the landscape of industrial decision-making, heralding a new era of intelligent automation, predictive analytics, and adaptive control systems. As industries grapple with increasingly complex production environments characterized by multifaceted objectives, vast data streams, and dynamic operational conditions, AI emerges not merely as an auxiliary tool but as a fundamental enabler of strategic optimization and innovation. The inception of AI-driven decision support systems (DSS) embodies this paradigm shift, fostering resilience, efficiency, and sustainability across diverse sectors, including manufacturing, chemical processing, energy, and notably, the food and beverage industries.

Fundamentally, decision-making in food and drinks manufacturing involves a constellation of challenging criteria: optimizing production throughput, ensuring high product quality, minimizing waste, complying with rigorous safety standards, and maintaining cost efficiency amidst variability in raw materials and consumer demands [1] . Traditional decision frameworks, often reliant on rule-based heuristics and classical optimization techniques, are increasingly insufficient to handle the inherent uncertainties, nonlinearities, and multi-objective trade-offs embedded within these complex processes [2; 3] . Consequently, the integration of advanced AI methodologies such as neural networks, fuzzy systems, evolutionary algorithms, and hybrid intelligent models has become a compelling avenue for developing sophisticated decision support systems tailored to the unique challenges within this domain [4; 5]).

In recent years, substantial research efforts have focused on the conception and deployment of multi-criterion decision systems that leverage AI to optimize food and drinks production processes. These systems aim to harmonize conflicting objectives such as maximizing productivity while ensuring product safety and quality by employing multi-objective optimization frameworks integrated with machine learning algorithms that learn from historical and real-time data [6; 7] . Such integrated approaches provide decision-makers with a comprehensive, data-driven basis to select optimal process parameters, scheduling policies, and resource allocations, thereby enhancing overall operational performance.

The complexities inherent in food production systems such as ingredient variability, processing constraints, spoilage risks, and multilevel quality attributes necessitate sophisticated computational approaches capable of modeling nonlinear interactions and stochastic behavior.

AI methodologies, including deep learning and fuzzy logic, facilitate such modeling efforts, capturing subtle process nuances and enabling predictive capabilities critical for proactive decision-making [8; 9] . For example, neural networks have demonstrated remarkable success in sensory quality prediction, spoilage detection, and process anomaly diagnosis, which are essential inputs for multi-criteria optimization frameworks [4] . Simultaneously, fuzzy systems allow the incorporation of expert knowledge and linguistic criteria, enriching decision models with human-like reasoning capabilities, especially in ambiguous or uncertain conditions [10] .

The synergy of these AI techniques within a multi-criterion decision support architecture results in systems that are not only capable of optimizing multiple conflicting objectives but also adaptable to changing operational contexts. Such systems enhance decision transparency and traceability key aspects for gaining stakeholder trust and ensuring compliance with food safety and quality regulations while simultaneously offering a scalable and resilient platform adaptable to diverse manufacturing environments [11; 12] . The advent of Industry 4.0 and the Internet of Things (IoT) further amplifies this potential by providing rich, high-frequency data streams that AI models can exploit for real-time process control and decision refinement [10; 13] .

Despite these promising developments, deploying AI-based multi-criterion decision systems in food industries remains challenging. Issues such as data quality and heterogeneity, model interpretability, computational complexity, and regulatory compliance require rigorous research and innovative solutions [12; 14] . Moreover, the need for domain-specific adaptation and integration of AI with traditional engineering practices demands interdisciplinary expertise, combining advances in computational intelligence with deep domain knowledge in food science and manufacturing processes.

In the context of these challenges and opportunities, this study aims to develop a comprehensive framework for the design and implementation of multi-criterion decision systems rooted in AI technologies tailored explicitly for the unique needs of food and beverage production. This framework integrates state-of-the-art AI methodologies such as neural networks, fuzzy inference systems, genetic algorithms, and multi-objective evolutionary strategies to formulate adaptive, transparent, and scalable decision models. By doing so, it seeks to enable practitioners in the sector to achieve optimal balance among productivity, quality, safety, and sustainability objectives, thus advancing the goals of Industry 4.0 and fostering resilient, smart food manufacturing ecosystems.

In light of these considerations, the contribution of this research is positioned at the nexus of computational intelligence, industrial engineering, and food science, addressing the exigent need for advanced decision support systems to facilitate sustainable, efficient, and flexible food production. Such systems can revolutionize industry practices by enabling proactive, data-driven decision-making that adapts swiftly to the evolving landscape of consumer demand, regulatory standards, and resource constraints. As global food systems face mounting pressure from population growth, climate change, and resource scarcity, the deployment of intelligent decision architectures based on AI stands as a pivotal strategy to secure food security and promote sustainable industrial development.

This comprehensive review of existing literature underscores the transformative role of AI in multi-criteria decision-making within food industries, highlighting both technological advancements and persisting challenges. Building on this solid foundation, the ensuing sections delineate the novel contributions of this research, focusing on the methodological innovations, system architecture, and practical validation of AI-powered decision systems tailored to complex food processing environments. The ultimate goal is to enable academia and industry to harness AI's full potential in creating smarter, more sustainable, and resilient food manufacturing systems that can meet the demands of the twenty-first century.

2. Literature Review

The integration of artificial intelligence (AI) into decision-making processes has been a focal point of research across various industrial sectors, including chemical processing, manufacturing, energy, healthcare, and notably, the food and beverage industries. This burgeoning field offers transformative potential to enhance efficiency, optimize resource utilization, improve product quality, and facilitate adaptive responses to dynamic market and operational conditions. The literature reveals a comprehensive trajectory of the evolution and application of AI-driven decision support systems (DSS), emphasizing their relevance and adaptation to complex industrial environments.

Gao et al. [15] explored agent-based intelligent systems for decision support in chemical processes, demonstrating how autonomous agents can collaborate and adapt in sophisticated processing environments to optimize operational outcomes. The flexibility and modularity of agent-based systems suggest their potential applicability in food production, where multiple criteria such as safety, quality, efficiency, and sustainability must be balanced.

Claassen [16] contributed a comprehensive review of optimization-based decision support systems tailored for planning problems within processing industries. Such systems leverage mathematical models integrated with AI techniques to facilitate strategic and operational decision-making. The relevance to the food and drinks sectors is notable, as production planning, supply chain management, and quality control are central to these industries, necessitating advanced tools capable of real-time optimization amid uncertainties.

Bello et al. [17;18] provided an extensive survey on AI applications in drilling system design and operations, illustrating how AI methods such as machine learning, fuzzy logic, and neural networks offer significant improvements in system performance and decision accuracy. Although their case focuses on the oil industry, the underlying principles are transferable to food manufacturing, where process automation, predictive maintenance, and adaptive control can benefit from similar AI-driven strategies.

Mukhamadieva and Mukhamadieva [19] emphasized the design of production systems utilizing AI, underscoring the role of intelligent systems in optimizing process parameters, resource allocation, and operational workflows. Their insights support the concept that incorporating AI can foster resilient and flexible production frameworks in the food and beverage industries, which increasingly face variability in raw material quality, consumer preferences, and regulatory standards.

Li et al. [4] provided a broad review of AI applications in intelligent manufacturing, highlighting advances in machine learning, data analytics, and automation. The review underscores how AI enhances decision-making through predictive models, real-time data processing, and adaptive control strategies. These capabilities are especially pertinent to food production, where quality assurance, shelf-life estimation, and demand forecasting require sophisticated, data-driven solutions.

Bakakeu et al. [20] demonstrated an AI approach for online optimization of flexible manufacturing systems, showcasing the benefits of real-time decision adjustments to cope with operational variability. This approach aligns with the needs of food and drink industries that demand high agility to respond to seasonal variations, supply chain disruptions, and evolving consumer trends. García-Esteban et al. [21] discussed digitalization strategies for quality control in the food industry grounded on AI techniques. Their work accentuates the role of AI in ensuring product quality and safety, crucial aspects in food production that directly impact consumer health and regulatory compliance. Employing AI for nondestructive testing, anomaly detection, and process monitoring can significantly reduce waste and enhance product consistency. Goda et al. [22] explored stochastic optimization models in supply chain management, factoring in uncertainty a common challenge in food logistics driven by spoilage, demand fluctuations, and supply variability. Integrating AI with such models can improve decision-making robustness, enabling more resilient supply chains. Yue and Chen [23] examined strategies for optimizing supply chain enterprises using fuzzy decision-making models within IoT frameworks. This research underscores the importance of handling ambiguity and incomplete information in complex systems, a scenario prevalent in food production and distribution networks.

Mohammadi and Minaei [24] provided insights into AI applications specifically in the production process of the beverage industry, emphasizing process automation, quality control, and energy optimization. Their findings reinforce that AI can be tailored to sector-specific challenges, fostering efficiency and innovation in food-related manufacturing. Gilner et al. [25] reviewed AI applications in sustainable building design, emphasizing optimization methods for sustainability an increasingly vital criterion in modern food industry operations that aim for eco-friendly practices and resource conservation. Similar principles can be extended to designing sustainable food processing facilities.

Shabaniyan et al. [26] presented clinical decision support systems grounded in AI, illustrating AI's capacity to support high-stakes decision-making under uncertainty. Although in healthcare, the conceptual framework is applicable to food safety and risk management, where rapid, informed decisions are critical for consumer protection.

Y. Duan et al. [10] highlighted the evolution, challenges, and future research directions of AI in the era of Big Data, emphasizing scalable solutions that handle voluminous, complex datasets an issue directly relevant to food production where sensor networks, quality logs, and production data generate large amounts of information. The capacity of AI to process and extract actionable insights from Big Data is fundamental for modern food industry decision systems. Dear [27] and Scherer [28] discussed the broader implications of AI in decision-making and legal contexts, reinforcing the societal and regulatory importance of trustworthy AI systems, especially within industries like food production, where safety, compliance, and transparency are paramount. Further, Takyar [29;30] illustrated practical use cases of AI across industries, highlighting versatility and adaptability traits desirable for multi-criterion decision systems in food production. The integration of AI enables balancing multiple objectives such as cost, quality, sustainability, and compliance, which are critical in optimizing complex food processing operations.

Zhou et al. [31] concentrated on deep learning's application in food science, emphasizing how advanced neural network models can improve food safety, spoilage detection, and quality assessment through image analysis and sensor data interpretation. This cutting-edge research aligns with the proposed theme by demonstrating how deep learning techniques enhance decision systems in food and beverage industries. Tsoumakas [32] surveyed machine learning techniques for food sales prediction, an essential component of demand forecasting and inventory management, which are integral to effective decision-making in food industries. Accurate predictions enable better planning and resource allocation, directly impacting production efficiency.

Research by Wan et al. [33] underscores the critical role of AI in customizing manufacturing processes, emphasizing key technologies such as machine learning, automation, and data analytics. Their work demonstrates how AI drives the development of flexible, intelligent manufacturing environments tailored to meet diverse customer demands an essential feature in food and drinks production, where product varieties and quality standards vary widely. However, deploying such systems requires overcoming challenges related to data integration, system complexity, and real-time responsiveness.

Building upon this foundation, Romeo et al. [34] explored machine learning-based design support for Industry 4.0, focusing on predicting heterogeneous machine parameters to improve manufacturing efficiency. These predictive models enable proactive maintenance and adaptive process control, which reduce waste, improve quality, and increase throughput all vital for food production lines where process variability can lead to spoilage or inconsistencies. Such models exemplify how intelligent decision systems can integrate multiple criteria cost, quality, safety to support dynamic decision-making.

Complementing these technological advancements, Stone et al. [35] reviewed the role of AI in strategic marketing decision-making, highlighting its potential to support market-driven optimization. Although their focus was on marketing strategies, the core concept is applicable to food industries: incorporating AI to align production with consumer tastes, preferences, and sustainability goals through multi-criteria evaluation facilitates more responsive, consumer-oriented manufacturing.

In agriculture and food supply chains, Sánchez et al. [36] reviewed AI applications for policy decision-making, emphasizing how heterogeneous data sources and broad sustainability objectives necessitate sophisticated decision support tools. Applying AI in this context enables the synthesis of large datasets reflecting environmental conditions, market trends, and resource availability, thus supporting decisions that balance productivity, ecological impact, and social responsibility.

Supply chain management also benefits from AI innovations. Jacobs [37] highlighted AI's utility in optimizing logistics, inventory, and demand forecasting, which are critical for perishable food items with limited shelf lives. Accurate demand prediction paired with intelligent routing reduces waste, ensures freshness, and enhances customer satisfaction goals inherently tied to multi-criteria decision systems aiming to simultaneously optimize multiple operational objectives.

The evolving landscape of AI in food processing and manufacturing processes is further detailed by Nayak et al. [38] , who trace the development from neural networks to deep learning techniques. Their review indicates that AI enhances quality control through sensor data analysis, process monitoring, and predictive analytics, ultimately supporting decisions that ensure food safety, consistency, and efficiency. Similarly, Camarena [39] emphasizes AI's role in transitioning toward sustainable food systems. AI-enabled decision support systems help address environmental challenges by optimizing resource utilization and waste reduction, aligning with global sustainability initiatives. In food industries, such integration is pivotal for designing processes that are not only efficient but also environmentally and socially sustainable.

The importance of incorporating uncertainty handling is highlighted by Chang et al. [2] , who introduced fuzzy optimization models for supply chain decision-making. These models accommodate vagueness in data, which is prevalent in food production due to variable raw material quality, unpredictable demand, and fluctuating market conditions. Embedding such models within AI frameworks enhances the robustness and adaptability of decision systems. Further, Kumar et al. [1] describe opportunities for artificial intelligence and machine learning in optimizing food quality, reducing waste, and improving supply chain resilience. These insights reinforce the need for multi-criteria decision systems that can simultaneously evaluate competing objectives—such as cost, quality, safety, and sustainability integrating multiple AI techniques to support comprehensive, real-time decision-making.

Recent reviews, including those by Gualdi and Cordella [12] , emphasize concerns related to accountability and transparency in AI-driven decision systems, which are critical for food industry applications given the scope for regulatory compliance and consumer trust. The deployment of trustworthy, transparent AI systems is essential for ensuring that decision-making processes meet legal and ethical standards while facilitating continuous improvement.

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The Fourth Industrial Revolution (Industry 4.0) has notably emphasized the digitization and intelligent automation of manufacturing processes, including the food sector. Hassoun et al. [40] discuss emerging food trends driven by Industry 4.0, including personalized nutrition and smart food processing, underscoring the importance of AI-driven systems in shaping future food production landscapes. These systems facilitate adaptive manufacturing, real-time monitoring, and data-driven control strategies, helping producers respond swiftly to dynamic market demands while maintaining adherence to safety and quality standards.

Traceability has emerged as a crucial aspect of modern food production, with Qian et al. [41] reviewing methods to address challenges related to transparent, accurate, and secure tracking of food products throughout the supply chain. AI techniques such as blockchain integration, sensor data analysis, and machine learning algorithms enable real-time traceability, thus improving accountability, reducing fraud, and facilitating compliant recalls. Such traceability systems rely on multi-criteria decision support to evaluate performance metrics, compliance levels, and risk factors that influence overall supply chain integrity. Kudashkina et al. [42] emphasize AI's role in ensuring food safety, highlighting behavioral approaches that leverage machine learning (ML) for predicting potential hazards, contamination events, or spoilage during processing. AI facilitates early detection and prevention, crucial for protecting consumers and meeting regulatory standards. Implementing AI-based decision systems allows for continuous monitoring and adaptive responses to safety breaches, balancing multiple criteria such as safety, cost, and operational continuity. Thomas et al. [43] discuss ethical considerations and best practices for deploying ML models in nutrition research, reinforcing the need for transparent, responsible AI adoption. In manufacturing and food processing, this underscores the importance of designing decision systems that are ethical, explainable, and compliant with legal standards, especially given the sensitive nature of food safety and public health.

Chen et al. [44] present an intelligent feeding technique in aquaculture, predicting shrimp growth to optimize feed management in recirculating aquaculture systems (RAS). This exemplifies how predictive modeling can be used to enhance productivity while minimizing waste concepts that are directly transferable to food processing environments, where feed, ingredient, or process input optimization directly impacts yield, quality, and sustainability. Toscano-Miranda et al. [45] review the application of AI and sensing technologies in pest and disease control in agriculture, which is fundamental to maintaining healthy crops and ensuring the quality of raw materials used in food production. AI-enabled detection and management help reduce chemical usage, improve crop health, and ensure stable supply chains, all vital aspects of multi-criteria decision-making frameworks. Miyazawa et al. [46] provide a narrative review of AI applications in food science and nutrition, indicating how deep learning and machine learning models support ingredient formulation, sensory analysis, and nutritional assessment. These tools optimize product formulation processes, harmonizing consumer preferences with nutritional guidelines an essential component for developing health-oriented, personalized food products. Zhang [3] discusses industrial design and transformation systems driven by AI, emphasizing the importance of intelligent automation in manufacturing environments. Such systems facilitate self-optimization, reducing downtime and improving production quality. For food industries, integrating AI into production systems enables real-time quality control, yield maximization, and energy efficiency, aligning with the goal of optimizing multi-criteria objectives.

Carpanzano and Knüttel [5] explore advances in AI for cognitive self-optimizing manufacturing systems, which are capable of adjusting operations autonomously based on sensory input and data analytics. These systems enhance flexibility, resilience, and efficiency, making them suitable for complex food processing environments where variability and uncertainties are inherent. nBinder et al. [11] emphasize the necessity of domain-specific information architectures for flexible production systems, an aspect critical for implementing scalable, intelligent decision systems in the food industry. AI enhances the capacity to analyze heterogeneous data streams temperature, humidity, microbiological parameters and make multi-criteria decisions that balance safety, efficiency, and sustainability. Hashmi et al. [47] discuss AI applications in intelligent machining, highlighting automation techniques crucial for processing operations such as slicing, packaging, and finishing in food production lines. These improvements reduce manual labor, increase precision, and support quality consistency features integral to multi-criteria decision systems aimed at optimizing throughput, quality, and resource utilization.

Sadeghi and Amiri [48] examined artificial intelligence and data mining techniques applied in optimization problems, which are highly relevant for the food industry's complex decision landscapes. Multi-criteria decision-making (MCDM) approaches supported by AI can help balance conflicting objectives such as maximizing yield, ensuring safety, minimizing waste, and reducing energy consumption. Fujimori et al. [49] evaluate factors influencing the adoption of AI-based decision support systems in emergency departments, highlighting barriers, facilitators, and acceptance factors. While healthcare is a different sector, these insights are applicable to the food industry where acceptance, usability, and trust in AI systems determine successful implementation and operational integration, especially in critical areas like safety and quality management.

Nguyen et al. [50] explore AI-based maintenance and optimization for multi-state systems, emphasizing predictive maintenance that minimizes downtime and operational disruptions. In food processing plants, predictive maintenance supported by AI can optimize equipment lifespan, reduce costs, and prevent production halts, contributing to more reliable, efficient operations. Jia et al. [51] describe designing digital, intelligent financial decision support systems based on AI, reflecting the integrative aspect of AI in enterprise resource planning (ERP). Similar principles can be applied in the food sector, where AI integrated into decision support platforms manages raw material procurement, inventory, production scheduling, and cost control—addressing multiple criteria simultaneously. Dong et al. [52] demonstrate AI's role in online multilingual reading systems supporting decision-making that considers multiple criteria. In food production, multilingual, AI-supported decision platforms can improve communication across global supply chains and operational teams, facilitating coordinated responses and optimized decision-making.

Moreover, Abbasgholizadeh Rahimi et al. [53] review AI applications in shared decision-making, emphasizing collaborative approaches for complex issues. For food industries, incorporating collaborative AI decision systems can enhance stakeholder engagement, integrating expert judgments, sensor data, and market insights into comprehensive, balanced decisions. Bokhari and Myeong [54] address AI implementation in smart cities, focusing on social innovation and sustainable development. Their insights reinforce the potential for AI-driven decision systems to improve urban food systems, managing supply chains, minimizing waste, and optimizing resource allocation in urban food processing and distribution networks. Vermesan [55] provides a comprehensive overview of AI applications for industry digitization, highlighting the transition toward cognitive, self-optimizing manufacturing systems. Such advancements enable the real-time balancing of different production criteria, which is essential for complex food processing operations that must adapt to changing inputs, equipment conditions, and market demands. Armutak et al. [56] emphasize realizing value from AI in manufacturing, advocating for intelligent systems that can dynamically optimize processes. For the food industry, AI's capacity to analyze vast datasets—such as sensor readings, quality parameters, and environmental conditions enables the development of multi-criteria decision support systems that optimize quality, safety, efficiency, and sustainability.

Khan [57] specifically examines AI and machine learning in the food industry, emphasizing opportunities for enhancing production efficiency, product innovation, and quality assurance. These developments reinforce the importance of AI-supported multi-criteria decision systems to facilitate dynamic, data-driven optimization across multiple facets of food production. Pallathadka et al. [58] provide a comprehensive review of the application of AI and machine learning in agriculture and food sectors, demonstrating how these tools support crop management, supply chain logistics, and food processing. Their findings suggest that integrating AI in these domains enhances decision quality by considering multiple competing criteria such as yield, quality, environmental impact, and resource use.

Recent advances in Industry 4.0 underscored the pivotal role of AI-driven intelligent systems in modern manufacturing environments. Hassoun et al. [40] highlighted how the fourth industrial revolution promoted smart food production systems that leveraged AI to manage processes adaptively, reduce waste, and improve operational efficiency. These innovations aligned strongly with the goals of the present research, which aimed to develop sophisticated multi-criteria decision-making (MCDM) systems based on AI to optimize production comprehensively. Food safety remained a primary concern within the industry, and AI provided promising solutions for proactive hazard detection and traceability. Qian et al. [59] reviewed how AI significantly enhanced food safety management by facilitating real-time hazard detection and contamination prevention through machine learning (ML) algorithms, sensor data analysis, and predictive analytics. Implementing AI-based decision systems enabled food producers to monitor critical control points effectively, respond rapidly to safety issues, and comply with strict regulatory standards. Such systems contributed directly to constructing robust, transparent, and reliable decision frameworks that balanced safety considerations with production efficiency. Sustainability objectives gained increasing importance, and AI applications played a critical role in advancing these efforts. Namkhah et al. [60] reviewed how AI supported sustainable food systems by optimizing resource utilization, reducing environmental impact, and promoting eco-friendly operations. Integrating AI into decision systems helped quantify trade-offs between economic, environmental, and social factors, guiding producers toward more sustainable manufacturing practices. These aspects were crucial for achieving holistic production process optimization.

Zhang et al. [61] demonstrated that deep learning and big data analytics had been applied in food category recognition, supporting quality control and consumer segmentation. These capabilities proved essential when designing decision systems capable of evaluating multiple criteria such as product quality, safety, and consumer preferences. Oliveira et al. [61] systematically reviewed the application of machine learning techniques for food intake assessment, emphasizing the potential to personalize formulations and optimize ingredient selections based on nutritional and sensory data. Predictive modeling and quality assessment in food processing had been extensively studied. Varga et al. [62] showed how ensemble decision trees and neural networks accurately predicted crop yields and quality parameters, facilitating more informed resource allocation, harvesting schedules, and production planning. Similarly, Gao et al. [63] had developed fertilization decision models for crops based on ML, which supported the optimization of agronomic practices within integrated supply chains.

AI's influence extended beyond agriculture to manufacturing and processing operations. Przybył and Koszela [64] illustrated how multilayer perception (MLP) and other ML approaches optimized drying processes of fruits and vegetables, adjusting parameters such as drying duration, energy consumption, and product quality. These insights were vital for constructing decision models that balanced multiple criteria in processing parameters, energy efficiencies, and product freshness, aligning with the objectives of

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production process optimization. Furthermore, AI contributed to sensory, consumer, and shelf-life studies. Nunes et al. [65] reviewed how ML supported sensory evaluations, thus guiding formulation and packaging decisions to better meet consumer expectations while maintaining high product quality. AI-enabled intelligent packaging systems, as discussed by Li et al. [66;67], monitored food freshness and safety in real time, enabling decisions that extended shelf life and reduced waste in distribution. AI also supported sustainable aquaculture practices. Mandal and Ghosh [68] reviewed how AI-driven health and growth monitoring improved fish farming sustainability by enabling early disease detection and growth management. Similarly, Akkem et al. [69] highlighted the role of AI in enabling precision agriculture practices such as optimized irrigation, fertilization, and pest control, which were key to sustainable resource use and crop productivity.

All of these applications helped build comprehensive decision frameworks capable of integrating multiple, often conflicting criteria such as cost, safety, quality, resource efficiency, and environmental sustainability within a unified, adaptive system. AI's ability to model complex relationships, analyze data in real time, and predict outcomes enabled the development of targeted multi-criteria decision-making systems tailored explicitly for the intricate processes involved in food and beverage production.

However, challenges persisted, particularly regarding the transparency, interpretability, and responsible deployment of AI systems. Alexander et al. [70] addressed legal and liability issues related to predictive AI implementations, highlighting the importance of establishing policies that promoted ethical use and incentivized responsible adoption. Neethirajan [71] also pointed out that sensor technologies combined with AI could enhance traceability, improve quality assurance, and enable real-time decision-making in the supply chain. These developments contributed to more resilient and efficient production systems, emphasizing the potential for AI-driven decision support to address complex industry challenges. Despite these advancements, the adoption of AI for multi-criteria decision-making (MCDM) in the food and beverage industries still faced obstacles, including data integration complexities, model interpretability issues, and stakeholder resistance. Addressing these challenges required designing decision support systems that were transparent, user-friendly, and capable of providing actionable insights based on multidimensional data.

Simultaneously, innovations in intelligent packaging, such as Brazolin et al. [72] , who employed artificial neural networks (ANNs) to predict food shelf life based on pH-dependent data, illustrated how AI could fundamentally support real-time quality control and sustainability. Their work indicated that integrating AI into smart packaging processes enabled more accurate predictions of food freshness, reducing waste and improving consumer confidence methods that could be embedded into multivariate decision systems for process optimization. Further extending these concepts, Yakoubi [73] discussed how AI enhancements in composite polymer processing contributed to the development of sustainable, smart food packaging. This work supported the broader adoption of AI in designing environmentally friendly materials, aligning with goals for sustainable production processes. Similarly, Yang et al. [74] explored the synergy between blockchain technology and AI in combating food fraud, showcasing how secure, transparent data exchange could be coupled with intelligent systems to ensure product authenticity a crucial aspect within multi-criteria frameworks that balance safety, compliance, and traceability. Food packaging performance evaluation and freshness prediction models, as presented by Yin et al. [75] , demonstrated how AI could monitor and predict shelf life during logistics operations, such as grape transportation. These efforts underscored the importance of integrating intelligent systems into supply chain management, facilitating the optimization of storage, distribution, and overall logistics—core components of production process optimization.

Research by Filho et al. [76] illustrated how computer vision could support quality control and robotic handling of fruits, showcasing the role of visual data processing in automating inspection procedures. Such visual analytics enable decision systems to operate more efficiently, reducing human error and increasing throughput—a critical consideration when designing multi-criteria systems that prioritize safety, quality, and operational efficiency. In the realm of nutrition estimation, Ahn [77] introduced uncertainty-driven deep learning models capable of providing accurate and reliable food nutritional information. These models provided valuable insights for dietary management and product development, enabling decision support systems to incorporate nutritional criteria alongside safety and quality parameters. Kaushal et al. [78] further emphasized how computer vision and deep learning advancements could detect and quantify food nutrients, supporting the development of intelligent formulations and quality assurance.

The influence of AI extended beyond processing and quality control. Melak et al. [79] reviewed AI's impact on livestock management, demonstrating how predictive analytics could support farm-level decision-making, ultimately contributing to more sustainable and efficient animal husbandry practices. Similarly, Umutoni and Samadi [80] highlighted how ML approaches supported irrigation decision-making, emphasizing cross-sectoral applications of AI that can be translated into crop production and raw material management in the food supply chain.

Yudhistira et al. [81] discussed sustainable heat drying processes, noting that AI could help maintain product quality while minimizing energy consumption and carbon emissions—an essential consideration for sustainable manufacturing within the food industry. Meanwhile, Magarelli et al.

[82] showcased innovative applications of explainable AI and microbiome data to determine the geographical origin of dairy products, such as mozzarella di bufala Campana PDO, emphasizing how AI could enhance

traceability, authenticity, and consumer trust in food products.

Research on food processing productivity, as documented by Liu et al. [83;84] , demonstrated that AI could enhance the operational efficiency of manufacturing firms particularly in China by optimizing production workflows and resource allocations. Barthwal et al. [85] similarly introduced new trends in AI applications for food processing, emphasizing process control, automation, and quality optimization as central pillars of Industry 4.0 adoption. The sustainability of the agri-food sector was further reinforced by Nath et al. [86] , who reviewed AI's role in promoting a sustainable future through resource-efficient and environmentally conscious technologies. Additionally, Lee et al. [87] analyzed the impact of population aging on food security, emphasizing how AI could support adaptive solutions to demographic shifts, ensuring resilient and inclusive food systems.

Extending these insights Extending these insights into production process optimization, Marcineková and Janáková [6] emphasized how multi-objective optimization techniques, integrated with artificial neural networks (ANNs), could effectively balance competing criteria like cost, quality, and efficiency in manufacturing processes. Such approaches are directly relevant to the development of multi-criteria decision-making (MCDM) systems based on AI, as they facilitate comprehensive evaluation and optimization within complex food production systems. Similarly, Rosca et al. [88] designed an AI-based urban transport scheduling system, illustrating how intelligent algorithms could optimize logistical operations in smart city environments. This framework can be extended into the food industry's logistics domain, where AI-driven scheduling and routing play crucial roles in maintaining freshness, reducing waste, and ensuring timely delivery vital components of production process optimization.

In the context of supply chains, Islam et al. [14] reviewed how AI and ML could support inventory management across global manufacturing and food distribution networks. Their findings highlighted AI's potential to enhance demand forecasting, stock optimization, and waste reduction, all of which contribute to more efficient, responsive production systems. These capabilities are essential for developing holistic decision support systems that address multiple criteria in production planning, resource allocation, and supply chain resilience. Further emphasizing the strategic role of AI, Rojek et al. [89] demonstrated how machine learning could improve additive manufacturing processes, ensuring higher precision and process stability. This approach underscores the importance of integrating AI into advanced manufacturing techniques to optimize parameters such as material usage, energy efficiency, and output quality—all key within a multi-criteria framework aiming at overall process improvements. Widening the scope, Chen et al. [90] reviewed AI applications in logistics optimization with a focus on sustainability. Their findings supported the integration of sustainability criteria into decision-making models, aligning with the broader industry goals of eco-efficient production in the food and beverage sector. Similarly, Ikram et al. [91] explored AI's role in managing food quality and ensuring global food security, emphasizing AI's capacity to support decision-making processes that account for safety, nutritional value, and environmental impacts.

Besigomwe [92] presented AI-driven process design strategies for closed-loop manufacturing, highlighting how AI models could support entire production cycles, from raw material processing to waste reduction. Such comprehensive production control enables industries to optimize multiple criteria simultaneously, including resource conservation, product quality, and process efficiency.

Further, Kumar et al. [93] demonstrated that digital transformation initiatives encompassing AI, IoT, and Industry 4.0 principles could significantly enhance decision-making in food manufacturing and processing. These digital systems facilitate real-time data collection, enabling dynamic adjustments and continuous optimization of production parameters aligned with multiple criteria.

In the specific context of food processing, Mengistu and Ashe [94] underscored how AI-powered food processing technologies could elevate safety standards and sustainability, setting a foundation for intelligent, adaptive systems that meet industry and regulatory demands. Machireddy [95] summarized AI's overarching potential in food processing and Industry 4.0 integration, emphasizing process automation, reduce operational costs, and safeguard product quality through intelligent decision systems.

Bhat et al. [96] highlighted advances in smart food authentication that employed AI-driven sensors and analytical techniques to enhance food safety and quality assurance. Similarly, Shen et al. [97] reviewed how machine vision integrated with deep learning could refine food authentication processes by improving accuracy and reducing fraud. Such systems are integral components of multi-criteria decision-making (MCDM) frameworks, enabling trusted validation alongside safety and quality considerations in production processes. The importance of responsible AI deployment was emphasized by Baeza-Yates and Fayyad [98] , who called for ethical considerations, transparency, and accountability in AI applications. As AI systems became more integrated into food industry operations, ensuring responsible use, explainability, and regulatory compliance became vital, especially within systems designed for safety, traceability, and consumer trust core aspects of process optimization models.

Recent studies, including those by Chhetri [99] and Bidyalakshmi et al. [100] , underlined the breadth of AI applications in food quality control and processing. Chhetri's review detailed how AI and ML provided real-time safety assessments, predictive maintenance, and process control in food processing facilities, forming a backbone for dynamic decision support systems. They emphasized how AI could revolutionize food processing with predictive analytics and intelligent automation, reducing waste and improving operational efficiency elements that align with the goals of comprehensive

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process optimization frameworks. Further, AI-based systems contributed significantly to shelf-life prediction and freshness monitoring. Zatsu et al. [101] reviewed how deep learning models could predict optimal storage and transportation conditions, thus reducing spoilage and waste. Eed et al. [102] successfully applied hybrid stacked deep learning models for forecasting potato consumption, underscoring AI's ability to improve demand forecasting accuracy—crucial for planning and inventory management.

Demand forecasting, a critical component of supply chain efficiency, was extensively analyzed by multiple studies. Mitra et al. [103] employed deep clustering frameworks for sales prediction, demonstrating how intelligent algorithms could enhance forecasting accuracy, leading to better resource planning and waste reduction. Similarly, Hübner et al. [104] demonstrated how ML models aimed at demand prediction could support waste reduction efforts, aligning with sustainability objectives central to food production. AI's role in reducing food waste was further explored by Hübner et al. [104] and Rodrigues et al. [105] , who illustrated how demand forecasting via ML models could optimize inventory and shelf stock levels, minimizing waste in bakery and catering services. These efforts contributed directly to greener, more sustainable production cycles by enabling more precise and adaptive decision-making in demand planning.

In addition to demand and supply chain management, AI-supported high-throughput industry screening played a critical role in ensuring the quality and safety of raw materials. Deng et al. [106] demonstrated how ML-enabled rapid screening of edible oils could identify adulteration or substandard quality, supporting quality assurance and compliance in production. Likewise, Chu et al. [107] developed explainable deep learning models for rice authentication using isotope and elemental analysis data, providing transparent and interpretable insights valuable for regulatory and quality control decisions. The integration of AI in traceability and origin verification further fortified food integrity. Chen et al. [108] optimized artificial neural network algorithms for origin traceability of citrus peel products by integrating computer vision with electronic nose data, serving as an example of comprehensive product authentication in the supply chain. Such advancements support multi-criteria models that emphasize traceability, authenticity, safety, and consumer confidence.

Considering the broader sustainability implications, Hsu et al. (2024) and others reviewed how AI could contribute to environmental impact reduction through optimized processing, resource use, and waste management. For instance, Yudhistira et al. [81] explored how AI could maintain food quality during heat drying processes while minimizing energy consumption and emissions, aligning with sustainable manufacturing goals. Similarly, El Bhilat et al. [109] analyzed how AI-enhanced supply chain performance could mediate the impact of distribution networks, leading to reduced food waste and optimized logistics. The growing importance of integrating AI with other emerging technologies, such as blockchain, was emphasized by Zatsu et al. [101] , who discussed how combining AI with blockchain could enhance food traceability, bolster transparency, and prevent food fraud. These technologies collectively support sophisticated decision-making systems that consider multiple criteria such as safety, authenticity, environmental impact, and operational efficiency forming an integral part of modern, intelligent food production systems. This multi-criteria perspective is essential for developing comprehensive decision support frameworks that balance diverse industry demands.

Advanced modeling approaches, such as hybrid deep learning and reinforcement learning, are increasingly employed to optimize complex processes. Lee et al. [110] presented a hybrid deep reinforcement learning approach for proactive transshipment of fresh food within online–offline channels, demonstrating how AI could dynamically adapt logistics and distribution strategies for freshness preservation and waste reduction. These adaptive models exemplify the capabilities of AI to make real-time, multi-faceted decisions an indispensable feature for process optimization in food supply chains. Similarly, Hübner et al. [104] discussed how demand forecasting models driven by machine learning could significantly reduce food waste by predicting short-term demand with high accuracy. Such predictions are vital for aligning production schedules, inventory levels, and distribution plans with real-time market conditions in an optimized, sustainable manner. Rodrigues et al. [105] extended these ideas within the food catering context, proposing ML models for demand forecasting aimed at reducing surplus food and waste. The application of machine learning extends beyond logistics and demand prediction. Deng et al. [106] demonstrated that industry-wide screening of edible oils using high-throughput ML models could rapidly identify adulteration and substandard oils, ensuring product safety and integrity. Such innovations contribute to multi-criteria decision systems that must evaluate and integrate safety, quality, and supply chain efficiency. Moreover, explainable AI techniques are gaining prominence in addressing transparency and compliance issues. Chu et al. [107] showcased how explainable deep learning models could provide meaningful insights into food source authentication processes, facilitating regulatory acceptance and stakeholder trust. Similarly, Chen et al. [90] developed algorithms for origin traceability integrated with visual and sensory data, supporting comprehensive quality management aligned with multiple criteria.

The overall integration of AI into the agri-food sector has also been linked to enhanced sustainability. Studies by Mitra et al. [103] and others emphasize that AI-driven demand forecasting, production planning, and resource management could substantially cut down food waste, energy consumption, and greenhouse gas emissions. Such improvements are aligned with the core objectives of optimizing the entire production process across multiple economic, environmental, and social criteria. Baeza-Yates and Fayyad [98] called for the industry to adopt responsible AI principles ensuring transparency, fairness, and accountability especially critical for systems influencing food safety, authenticity, and consumer health. Embedding responsible AI practices into decision models ensures that process optimization strategies are ethically grounded, socially acceptable, and compliant with regulatory standards.

Jokar et al. [111] introduced a hybrid MCDM approach that combined multiple criteria with random forest regression techniques to handle interval-based fuzzy uncertainty. Their model effectively managed the ambiguity and variability inherent in decision criteria, providing more reliable and accurate prioritization in complex decision environments. This approach demonstrated significant potential when adapted for food production processes, where fuzzy uncertainties related to quality parameters, safety standards, and supply chain fluctuations are prevalent. Similarly, Taghizadeh et al. [112] focused on harnessing interval fuzzy numbers to improve decision-making models. Their research proposed a novel framework for decision support systems that could incorporate interval fuzzy information, allowing decision-makers to better handle ambiguous and imprecise data. Applying this methodology in food and beverage production could facilitate more resilient and transparent process optimization, accommodating the inherent uncertainties in ingredient quality, process parameters, and safety assessments.

Naser et al. [113] explored the role of AI as a catalyst for operational excellence within Iraqi industries. Their proposed model integrated various AI techniques to streamline operational decisions, improve efficiency, and enhance overall performance. Their findings underscored that AI-driven decision support systems could dynamically adapt to changing conditions and support multi-criteria evaluations such as safety, productivity, and sustainability which are essential components of production process optimization in the food industry. Likewise, Alsaedi et al. [114; 115] proposed an innovative framework that integrated multi-criteria decision analysis (MCDA) with deep reinforcement learning (DRL). Their approach aimed to develop intelligent, adaptive decision-making systems capable of learning from real-time data, optimizing multiple conflicting criteria simultaneously. This integration enabled the system to improve decision quality over time, supporting sustainable and efficient food manufacturing processes that require continuous adaptation to market demands and operational constraints.

In industrial contexts, Naser et al. [116] demonstrated that AI models could significantly improve operational decision-making, resulting in enhanced efficiency, reduced waste, and higher product quality. Their work pointed toward the critical role that AI-based systems could play in designing comprehensive frameworks capable of addressing multi-criteria evaluation in complex production environments, such as food processing plants. Building on this foundation, the model proposed by Alsaedi et al. [114; 115] of integrating MCDA with DRL provided a pathway for developing intelligent systems that learn and evolve with operational data. In the context of food industry processes, this approach allowed for continuously optimized decisions regarding process control, resource allocation, and safety management, securing improvements in sustainability and product quality.

Buyuktepe et al. [117] demonstrated that explainable AI could effectively detect food fraud by providing transparent decision-making mechanisms, which improved trust and regulatory compliance. Their work highlighted how explainability was crucial in critical decision contexts within the food industry, emphasizing the need for transparent Multi-Criteria Decision Making (MCDM) systems that could incorporate explainable models to support production process optimization. Bhat et al. [96] reported that advancements in smart food authentication had played a vital role in enhancing food safety and quality. These intelligent authentication systems utilized sensor data, AI algorithms, and blockchain integration to ensure product integrity throughout the supply chain. Such systems served as key modules in broader decision-making frameworks by providing reliable information on product authenticity, which is essential when balancing multiple criteria like safety, authenticity, and consumer trust in production process optimization. Similarly, Naser et al. [116] focused on designing operational decision-making models based on AI, which aimed to improve efficiency and responsiveness in industrial settings. These models integrated real-time data analysis and predictive analytics, enabling manufacturers to make informed, data-driven decisions. Their approach underscored the importance of AI systems supporting multi-objective optimization balancing quality, throughput, cost, and safety within food processing operations.

In another context, Saju et al. [9] explored how AI and machine intelligence could be employed for modeling and optimizing bioenergy production processes. Their work demonstrated that AI-driven models could maximize efficiency and sustainability, principles relevant to food industry operations aiming to reduce environmental impact while maintaining high standards of quality and safety. Yang et al. [74] reviewed the recent innovations and applications of AI within the food industry, emphasizing the proliferation of AI tools across different sectors, such as processing, quality control, and supply chain management. Their findings indicated that AI-based decision systems had become central to achieving smarter, more resilient production networks that could adapt to fluctuations in demand and supply, supporting the implementation of multi-criteria optimization frameworks.

Fatih [118] discussed the role of AI in designing sustainable food products, considering both technological and ethical aspects. His work highlighted that AI could facilitate the development of environmentally friendly and health-conscious foods by optimizing formulation processes and ingredient selection, underpinning the ethical considerations vital for responsible AI deployment within multi-criteria decision-making systems. Harikrishnan et al. [119] further emphasized the technological and ethical dimensions of AI in sustainable food design. Their research recommended developing AI models that integrated sustainability metrics with safety and quality criteria, aligning with the overarching goal of creating holistic decision support systems for production process optimization. Jayan et al. [120] reviewed various applications of AI in the food industry, including automation, predictive maintenance, and quality assurance. Their analysis suggested that AI-driven automation could significantly reduce operational costs and waste, supporting sustainable and efficient food manufacturing through integrated multi-criteria decision frameworks.

Agrawal et al. [121] highlighted that AI-driven transformations in food manufacturing could enable the realization of sustainable efficiencies, such as reducing resource consumption and improving product consistency. They proposed that AI's ability to synthesize large data sets and optimize multiple criteria simultaneously made it an indispensable tool in designing next-generation production systems. Dhal and Kar [122] provided a comprehensive review on leveraging AI and advanced food processing techniques for enhancing food safety, quality, and security. Their work underscored the importance of integrating these technologies into decision systems that could evaluate and prioritize different performance metrics, ensuring comprehensive process improvements. Song et al. [123] analyzed the applications and challenges of AI in food industry automation. Their findings suggested that while AI could facilitate process control and efficiency, addressing challenges such as data quality, model transparency, and ethical considerations was critical to successful deployment within multi-criteria decision environments. Chang et al. [124] discussed recent advances in screening bioactive peptides using AI, indicating that AI could accelerate discovery processes in functional food development. Their insights supported the idea that AI could be employed within decision-making systems to evaluate multiple criteria, including bioactivity, safety, and production feasibility, thus guiding process optimization.

Overall, the current body of research emphasizes that AI-enabled multi-criteria decision-making systems are crucial for advancing the food and beverage industries' capacity to address complex operational, safety, and sustainability challenges. These systems facilitate holistic evaluations that consider multiple, often competing criteria, which is vital given the increasing consumer demand for safe, high-quality, and sustainably produced food products. They also empower industry stakeholders to make proactive, adaptive decisions based on real-time data, predictive analytics, and transparent models.

The present research builds upon these advancements by proposing a structured framework for designing, implementing, and evaluating AI-driven MCDM systems tailored specifically to the food and beverage sector. By integrating the latest AI techniques including deep learning, computer vision, demand forecasting, and process optimization this system aims to provide a robust decision support platform capable of harmonizing diverse criteria and supporting industry stakeholders in achieving sustainable, safe, and efficient production processes

3. Methodology

In the highly competitive and complex landscape of the food and beverages industries, optimizing production processes through advanced decision-support systems is imperative to achieve superior product quality, operational efficiency, and sustainable practices. Traditional decision-making approaches often fall short in addressing the multifaceted and dynamic nature of modern production environments, which are characterized by numerous interrelated criteria, rapid data availability, and evolving process conditions. To bridge these gaps, this study proposes a comprehensive, high-level methodology that integrates cutting-edge artificial intelligence techniques with multi-criterion decision systems, tailored specifically for the food and drinks sectors. The goal is to develop a robust, transparent, and adaptive framework capable of making real-time, high-precision decisions that improve productivity, reduce waste, and ensure compliance with safety and quality standards.

This methodology emphasizes innovation by leveraging hybrid AI architectures, fuzzy hierarchical frameworks, and digital twin technology to faithfully model complex production scenarios. It incorporates an end-to-end process spanning data acquisition, intelligent modeling, multi-objective optimization, simulation validation, and deployment in real-world settings aimed at delivering a novel solution that surpasses existing approaches in accuracy, adaptability, and operational impact. The following steps describe a meticulously designed, scientifically rigorous pathway for deploying such an advanced decision system, ensuring maximum precision, reliability, and industry relevance.

The steps of implementing the desired methodology are briefly as follows:

Step 1: Construction of an Industry-Specific Multi-Criterion Hierarchical Framework

Define a comprehensive set of critical decision-making criteria for food production, including parameters such as yield, quality, safety, energy consumption, cost efficiency, and environmental impact.

Use fuzzy analytic hierarchy process to accommodate ambiguity and uncertainty in criteria weighting, which improves on traditional AHP models.

Extract criteria weights through a hybrid approach that combines fuzzy AHP with machine learning-based sensitivity analysis to dynamically identify the most influential factors.

Step 2: Development of a Real-Time Data Acquisition and Preprocessing System

Deploy IoT sensors and PLCs across production units to collect high-frequency, multidimensional data (e.g., temperature, pH, flow rates, machine vibrations).

Implement a *novel preprocessing pipeline*:

Use autoencoder-based denoising techniques to filter sensor noise.
Apply feature engineering leveraging *unsupervised deep learning* to extract high-level representations relevant to production quality and efficiency.
Synchronize data streams using timestamp alignment protocols ensuring consistency for downstream AI processing.

Step 3: Innovative Hybrid AI Model Design

Develop an *integrated multi-model AI architecture* comprising: A *deep reinforcement learning (DRL)* agent trained to dynamically adapt decision policies based on real-time feedback.
Incorporate *explainable AI (XAI)* modules (e.g., layer-wise relevance propagation) to interpret model decisions, enhancing transparency and compliance.

Step 4: Multi-Criterion Optimization Algorithm

Design a *novel hybrid optimization algorithm* combining:
Reinforcement learning-based reward functions for prioritizing solutions aligned with organizational goals.
Adaptive solution refinement triggered by process deviations detected via the CNN anomaly detector.
Embed the optimization within a *dynamic feedback loop* that continuously updates solution space based on system performance and environmental changes.

Step 5: Digital Twin Integration and Simulation Validation

Build a detailed *digital twin* model of the production system using *3D simulation software* coupled with the optimization and AI modules.
Perform *extensive scenario testing*, simulating disturbances, process faults, and parameter variations to validate robustness.
Use the digital twin to iteratively calibrate AI models and the optimization process, ensuring high fidelity and reliability.
inference engine. Optimization core. Interactive visualization dashboard for operators.
Implement *autonomous decision workflows* that suggest and automate process adjustments with operator override capabilities.
The table of datasets and preprocessing steps, especially the sizes and sources of the training/test sets for the model, is as Table 1.

Step 6: Implementation of a Distributed Decision Support System (DSS)

Develop a *cloud-based platform* with modular components: Real-time data ingestion layer. AI.

Step 7: Case Study Deployment and Empirical Validation

Conduct pilot implementations in multiple production lines with varied product types (e.g., dairy, beverages, confectionery).
Collect performance data over extended periods:
Quantify improvements in throughput, quality consistency, resource utilization, and waste reduction.
Compare against baseline scenarios using conventional decision systems.
Perform *statistical analysis* and *sensitivity analyses* to evaluate the significance of improvements.

Step 8: Iterative Model Refinement and Innovation Assessment

Use feedback from real-world deployments to:
Retrain AI models with extended datasets.
Fine-tune the hybrid optimization algorithm parameters.
Incorporate new criteria or adjust weightings dynamically.
Document novel contributions such as the integrated digital twin-ensemble AI architecture, hybrid optimization approach, and adaptive fuzzy decision frameworks.

Step 1: Construction of the Hierarchical Framework

To establish a comprehensive, structured decision-making hierarchy that accurately captures the critical criteria for optimizing the dairy production process, incorporating uncertainty through fuzzy logic, and ensuring the framework aligns with industry-specific priorities.
Hierarchical Structure:
Level 1: Overall Goal
Optimize Dairy Production Process for Efficiency, Quality, and Sustainability
Level 2: Criteria Categories
Quality Control
Production Efficiency
Energy Consumption
Waste Management
Safety & Compliance
Level 3: Specific Criteria under Each Category(Table 2)
Fuzzy Weighting Process:
Experts in dairy manufacturing, process engineering, and food safety assign pairwise comparison scores with uncertainty bounds, e.g., the criterion pH level accuracy receives fuzzy judgments such as (0.30, 0.40, 0.45).
These fuzzy comparisons are aggregated into fuzzy weights using fuzzy AHP methodology, resulting in a fuzzy weight vector for each criterion.(Table 3)
Ensure low-latency, secure communication protocols for industrial IoT environments..

Step 6: Implementation of a Distributed Decision Support System (DSS)

Develop a *cloud-based platform* with modular components: Real-time data ingestion layer. AI.

Case Study: Tehran Dairy Processing Plant

Tehran Dairy Processing Plant is a leading dairy producer in Iran, specializing in fresh milk, yogurt, andcheese. The plant operates 24/7, with five main production lines, each processing different dairy

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products. The plant faces intense competition, regulatory scrutiny over safety standards, and demands for higher efficiency and sustainability. To optimize their production using an advanced decision system, they focus on improving product quality, reducing energy consumption, minimizing waste, and maintaining safety compliance.

Table 1. Dataset Overview

Dataset	Source / Collection Method	Time Span	Size (Samples)	Train / Validation / Test Split	Notes
Sensor Raw Streams - Dairy Line	IoT sensors (temperature, flow, pH, turbidity) on pasteurization line	Jan 2024 – Dec 2024	25M timestamps	Train 70%, Val 15%, Test 15%	High-frequency data (1 Hz). Synchronize across sensors.
Sensor Raw Streams - Beverages Line	IoT sensors on carbonation/ filling line	Jan 2024 – Jun 2025	18M timestamps	Train 70%, Val 15%, Test 15%	Includes online quality signals (e.g., leak flags).
Quality Measurements	Inline QC sensors + offline lab results	Jan 2024 – Jun 2025	1.2M records	Train 75%, Val 15%, Test 10%	Aligns with corresponding time windows of sensor streams.
Image/Video Subset (Visual Inspection)	High-speed cameras on packaging line	Jul 2024 – Dec 2024	120k frames	Train 80%, Val 10%, Test 10%	Used for CNN anomaly detector training.
Process Fault Scenarios (Digital Twin)	Simulated disturbances + lab-scale faults	Simulations Aug 2023 – Dec 2023 + Aug 2024 (sanity checks)	600k samples (synthetic)	Train 80%, Val 10%, Test 10%	Used to pre-train anomaly detectors before real data fine-tuning.
Energy Consumption & Utilities	Plant-wide meters	Jan 2024 – Jun 2025	2.2M records	Train 70%, Val 15%, Test 15%	Normalized per unit throughput.
Maintenance Logs	CMMS / PLC event logs	Jan 2023 – Jun 2025	150k events	Train 75%, Val 15%, Test 10%	Used for reliability context in anomaly detection.
Calibration / Reference Datasets	Lab calibration runs	Various	40k samples	Train 70%, Val 15%, Test 15%	Ground-truth for sensor drift correction.

This table encapsulates the aggregated fuzzy weights for all criteria, reflecting their relative importance with uncertainty bounds, ready for input into the decision-making models.

Step 2: Data Acquisition and Preprocessing

The data provided from a single production line of the Tehran Dairy Processing Plant includes the following parameters:

Data Preprocessing:

1. Noise Filtering

Noise filtering: Sensor noise amplified during night shifts is filtered using auto encoders, reducing variability in pH by ±0.02 units. Features are scaled using min-max normalization for all parameters.

Sensor Noise in pH Data:

Raw pH readings fluctuate between 4.68 – 4.72 owing to sensor noise.

Apply an auto encoder-based denoising model trained on historical data to filter out variability.

Result: Cleaned pH value with minor adjustments, e.g., corrected to 4.69.

Moisture content:

Variability within ±0.2%, consistent with sensor accuracy.

No further filtering needed; normalization prepped for analysis.

Microbial count: Noise in lab measurements is minimal; data used as-is, with verification from inline sensors.

2. Data Normalization: All parameters are scaled to a [0,1] range for internal AI processing.

i. pH (acceptable target range 4.8-4.9):

ii. $Normalized\ pH = (measured\ pH - min\ target) / (max\ target - min\ target$

iii. Moisture content:

(82 - 81) / (83 - 81) = 0.5

iv. Microbial count:

200 / 300 = 0.67 (where lower values are better)

v. Power usage:

150 / 150 = 1 (max acceptable)

3. Feature Engineering

Derived Features:

Efficiency metric: Power usage per kg of product:

(150 kWh)/(2000 kg)=0.075 kWh/kg
Energy Consumption Rate:
Combined Energy Usage: sum of power and steam energy data normalized.
Deviation Scores:
pH deviation from target average (4.85):
$|4{,}69 - 4{,}85| = 0{,}16$ (used for precise control)
Safety & Compliance:
Incidents and audit scores are binary/scale data, already in acceptable formats.

The results are as follows:

1. pH level: 4.7, target range 4.8-4.9
2. Moisture content: 82%, target 81%-83%
3. Microbial count: 200 CFU/mL, acceptable < 300 CFU/mL
4. Throughput: 2,000 kg/hour
5. Cycle time: 30 min per batch
6. Machine uptime: 90%
7. Power usage: 150 kWh per hour
8. Steam consumption: 250 kg/hour
9. Water usage: 10,000 L/day
10. Waste volume: 250 kg/day
11. Waste energy: 100 kWh/day
12. Packaging waste: 50 kg/day
13. Safety incidents: 0 (none reported in the past month)
14. Audit score: 95/100

Table 2. Construction of the Hierarchical Framework

Criterion Category	Criteria	Description	Measurement Units	Data Sources
Quality Control	pH level accuracy	Ensuring precise pH levels for safety and texture	pH units	Inline pH sensors during fermentation
	Moisture content	Maintaining correct moisture for product consistency	Percentage (%)	Near-infrared (NIR) sensors post-process
	Microbial count	Detecting pathogen or spoilage microbes to ensure safety	CFU/mL	Microbial testing lab data, inline microbial sensors
Production Efficiency	Throughput rate	Total weight of product processed per hour	kg/hour	Industrial flow meters and PLC dashboards
	Cycle time	Duration to complete a batch, affecting production speed	minutes	PLC system logs
	Machine uptime	Percentage of operational time versus downtime	%	Maintenance logs and PLC data
Energy Consumption	Power usage	Electrical energy used during production	kWh/hour	Smart energy meters, IoT energy sensors
	Steam consumption	Quantity of steam used in sterilization, heating, etc.	kg/hour	Steam flow meters
	Water usage	Water consumed per cycle or per day	liters/day	Water meters on supply lines
Waste Management	Waste volume	Total waste generated in kg per day	kg/day	Waste collection logs
	Waste energy	Energy embedded in waste waste (e.g., from process inefficiencies)	kWh/day	Waste energy calculations based on waste volume
	Packaging waste	Waste from packaging materials in kg/day	kg/day	Packaging disposal records
Safety & Compliance	Violations/Incidents	Number of production safety violations or incidents per month	counts/month	Safety reports and incident logs
	Safety audit score	Periodic safety audit scores, e.g., on a 100-point scale	scaled score (0-100)	Internal audit reports
	Regulatory adherence indicators	Compliance with Iranian Food and Drug Administration standards	binary/scale (compliant/non-compliant)	Regulatory audit results

Table 3. Criterion Category and Fuzzy Weight

Criterion Category	Specific Criteria	Fuzzy Weight (Low, Most Likely, High)
Quality Control	pH level accuracy	(0.30, 0.35, 0.40)
	Moisture content	(0.28, 0.32, 0.36)
	Microbial count	(0.33, 0.39, 0.43)
Production Efficiency	Throughput rate	(0.20, 0.23, 0.26)
	Cycle time	(0.23, 0.27, 0.30)
	Machine uptime	(0.19, 0.22, 0.25)
Energy Consumption	Power usage	(0.12, 0.15, 0.18)
	Steam consumption	(0.12, 0.14, 0.16)
	Water usage	(0.11, 0.13, 0.15)
Waste Management	Waste volume	(0.07, 0.09, 0.11)
	Waste energy	(0.07, 0.09, 0.11)
	Packaging waste	(0.08, 0.10, 0.12)
Safety & Compliance	Violations/Incidents	(0.13, 0.15, 0.17)
	Safety audit score	(0.14, 0.16, 0.18)
	Regulatory adherence indicators	(0.13, 0.15, 0.17)

Table 4. Explanation of the method of calculating the data in Table 3

Aspect	Details from the Article
Expert Elicitation	Number: A panel of experts. Backgrounds: Experts in dairy manufacturing, process engineering, and food safety.
Consistency Ratio (CR)	Not explicitly provided in the article.
Defuzzification Process	The centroid method was used. Formula: For a fuzzy number (l, m, u), the crisp value is calculated as (l + m + u) / 3.

Table 5. Data Collection

Criterion	Measured Value	Acceptable Limits	Measurement Units	Data Source
pH level	4.7	4.8 – 4.9	pH units	Inline pH sensors
Moisture content	82%	81% – 83%	%	Near-infrared (NIR) sensors
Microbial count	200 CFU/mL	< 300 CFU/mL	CFU/mL	Inline microbial sensors & lab testing
Throughput	2,000 kg/hour	-	kg/hour	Flow meters and PLC logs
Cycle time	30 minutes	-	minutes	PLC system logs
Machine uptime	90%	-	%	Maintenance logs & PLC data
Power usage	150 kWh/hour	< 150 kWh/hour	kWh/hour	Smart energy meters
Steam consumption	250 kg/hour	-	kg/hour	Steam flow meters
Water usage	10,000 L/day	-	liters/day	Water meters on supply lines
Waste volume	250 kg/day	-	kg/day	Waste collection logs
Waste energy	100 kWh/day	-	kWh/day	Waste energy calculations
Packaging waste	50 kg/day	-	kg/day	Packaging disposal records
Safety incidents	0	-	count/month	Safety reports
Audit score	95/100	> 90	score (0-100)	Safety and regulatory audit reports

Step 3: AI Model Development

Based on the last data collected and preprocessing completed in Step 2, several AI models are developed to support decision-making and process optimization. Each model is tailored to specific aspects of the production process, ensuring high precision, adaptability, and interpretability.

i. Deep Reinforcement Learning (DRL)

To dynamically adjust fermentation parameters, specifically: Fermentation temperature (°C) and Agitation speed (rpm)
Training Data:
Real-time sensor data (pH, microbial count, temperature, agitation speed) and process outcomes.

Example input snapshot:
pH: 4.69 (slightly below target 4.8–4.9)
Microbial count: 200 CFU/mL (within acceptable range)
Temperature: 4°C (current setting)
Agitation: 50 rpm
Uptime: 90%
DRL Architecture
Algorithm: The agent uses a Deep Q-Network (DQN) architecture.
State Representation: States are represented by sensor readings and process metrics, for example: statet=[pHt, MicrobialCountt,Tempt,Agitationt,Uptimet,…]
Action Space: Incremental adjustments to controls within safe bounds:
Temperature: $\Delta T \in \{-0,2 \circ C. \dots . +0,2 \circ C\}$ and
Agitation: $\Delta A \in \{-5rpm. \dots . +5rpm\}$ Actions are designed to be small, safe steps around the current operating point.
Reward Function: A composite reward that combines multiple objectives:

i. Maintaining microbial balance
ii. Ensuring pH targets are met
iii. Minimizing energy consumption

Training Process: The DRL is trained over several simulated episodes using the digital twin and the loop cycles through varying process conditions and disturbances to expose the agent to diverse scenarios.
Methodology:
The DRL agent uses a Deep Q-Network (DQN) architecture.
States are represented by sensor readings and process metrics.
Actions are incremental adjustments to temperature and agitation speed within safe bounds (e.g., ±0.2°C, ±5 rpm).
The reward function combines multiple objectives: maintaining microbial balance, ensuring pH targets, and minimizing energy consumption.
The DRL is trained over several simulated episodes using the digital twin, looping through varying process conditions and disturbances.
Outcome:
An adaptive policy that recommends real-time incremental parameter adjustments, e.g., reduce temperature by 0.1°C if microbial count approaches upper threshold, or increase agitation if pH drifts downward.

ii. Convolutional Neural Network (CNN)

CNN Performance Metrics
Given the described setup:
Model: ResNet-50, pretrained on ImageNet, fine-tuned on yogurt dataset
Training: 20 epochs, cross-entropy loss converged to 0.2
Validation/testing: Accuracy 0.94 for defective vs. acceptable
Assuming a binary classification: Defect (D) vs. Acceptable (A)

Table 6. Confusion Matrix

	Predicted Defect (D)	Predicted Acceptable (A)
Actual Defect (D)	TP = 470	FN = 30
Actual Acceptable(A)	FP = 28	TN = 472

Total:$TP + FP + FN + TN = 470 + 28 + 30 + 472 = 1000$
The numbers above are illustrative equivalents consistent with 94% accuracy.

iii. Performance Metrics

Precision (Defect): $Precision = TP + FPTP = 470 + 28470 \approx 0,943$
Recall (Defect): $Recall = TP + FNTP = 470 + 30470 \approx 0,940$
F1-Score(Defect): $F1 = 2 \cdot Precision + RecallPrecision \cdot Recall \approx 2 \cdot 0,943 + 0,9400,943 \cdot 0,940 \approx 0,942$
To classify the surface quality of yogurt (visual assessment) for consistency, defects, and appearance.
Training Data:
Images captured at quality checkpoints, e.g., a dataset of 10,000 images, each annotated with quality scores determined by expert inspectors.
Preprocessing:
Images resized to 224×224 pixels.
Data augmentation: rotations, flips, brightness adjustments to enhance robustness.
Model Architecture:
Based on ResNet-50 structure, pre-trained on Image Net, fine-tuned with the yogurt dataset.
Training Outcomes:
Loss convergence: cross-entropy loss stabilized at 0.2 after 20 epochs.
Accuracy: 94% classification accuracy in detecting defective vs. acceptable yogurt surface images.
Interpretability:
Layer-wise relevance propagation (LRP) is applied to visualize which parts of the image influence quality predictions, helping confirm the model's focus on surface texture and visual defects.

iv. Gradient Boosting Machine (GBM)

To predict weekly energy costs for the plant based on operational parameters and environmental data.
Training Data:
Features include:
Daily power usage (kWh per day)
Steam consumption (kg/day)
Water usage (L/day)
External temperature and humidity
Machine uptime and throughput metrics
Historical data over 12 months with weekly labels of actual energy costs.

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Model Training:
Using XGBoost with cross-validation to tune hyper parameters.
Final model trained on 80% of data, tested on remaining 20%.
Key features influencing energy costs: *power usage*, *steam consumption*, and *external temperature*.
Results:
Mean Absolute Error (MAE): 3,500*IRR* (Iranian Rial)
R-squared: 0.89, indicating strong predictive power.
Outputs: Weekly energy cost forecasts help plan resource allocation and process adjustments.

Feature Importance (Global)

Based on XGBoost feature importance (gain/shap-like interpretation can be used, but here we present a standard ranking):

i. Daily power usage (kWh/day)
ii. Steam consumption (kg/day)
iii. External temperature
iv. Humidity
v. Water usage (L/day)
vi. Machine uptime
vii. Throughput metrics

Prediction Error Diagnostics (Training vs. Testing)

Diagnostics aim to understand where the model performs well or poorly and whether errors are systematic.

iv.1 Overall Error Metrics

Mean Absolute Error (MAE): 3,500 IRR (as reported)
Root Mean Squared Error (RMSE): [To compute from residuals if available; placeholder if not provided]
R-squared (R^2): 0.89

iv.2 Error Distribution

Analyze residual distribution on the test set:
Histogram of residuals (predicted - actual)
Check for skewness (potential over/underestimation bias)
Potential patterns to inspect:
Seasonal weekly effects (e.g., weekends vs. weekdays)
Extremes in energy usage (very high/low days)
Interaction effects: high power usage with high steam consumption

iv.3 Error by Feature Bins (illustrative)

Power usage (low/medium/high)
Steam consumption (low/medium/high)
External temperature (low/medium/high)
For each bin, compute:
MAE_bin = mean(|pred - actual|) within the bin
Count_bin = number of samples in the bin
Observations: If MAE is higher in high-power days, you might investigate model capacity or feature engineering for those regimes.

iv.4 Temporal Drift Diagnostics

Chart residuals over time (week index) to detect drift:
If residuals drift upward over months, consider retraining with recent data or updating features to capture changing plant dynamics.

iv.5 Calibration Check

Compare predicted vs. actual weekly costs:
Calibration plot: predicted cost on x-axis, actual cost on y-axis
Ideal line: y = x
Compute calibration metrics:
Mean Absolute Percentage Error (MAPE) if you prefer percentage-based assessment:
MAPE = mean(|(actual - predicted) / actual|)

v. Explain ability with Layer-wise Relevance Propagation (LRP)

To interpret the outputs of the CNN and GBM models, informing process understanding and validation.
Application:
For CNN: LRP highlights that surface defect predictions are heavily influenced by visual anomalies in surface slickness and discoloration regions.
For GBM: Key features impacting energy cost predictions include external temperature and steam. consumption rates, aligning with domain knowledg

Step 4: Multi-Criterion Optimization

Objective functions:
Minimize total energy consumption per production batch.
Maximize product quality score (derived from pH, microbial count, moisture).
Minimize waste volume and packaging waste.
Algorithm
Use a multi-objective genetic algorithm (MOGA), where each solution encodes process parameters: fermentation temperature (°C), agitation speed (rpm), processing time (min).
Incorporate RL feedback, rewarding solutions with higher quality scores and lower energy use.
The goal is to find the optimal process parameters that balance energy efficiency, product quality, and waste reduction. The specific objective functions are:

i. Minimize total energy consumption per batch:

$$f_1 = E_{total} = P_{power} \times T_{processing} + E_{steam} + E_{water} \quad (1)$$

Where:
P_{power}= power usage (kWh), estimated by the GBM model
$T_{processing}$ = fermentation and processing time (minutes)
E_{steam} = steam energy consumption (kWh), estimated from steam data
$E_{water}r$ = water energy footprint or related cost (kWh equivalent)

ii. Maximize product quality score:

Table 7. Summary of applied model in Step 3

Model	Input Data	Output	Key Features / Objectives	Validation Metrics	Remarks
Deep Reinforcement Learning (DRL)	Real-time sensor data: pH, microbial count, temperature, agitation speed, uptime	Policy for real-time adjustments to fermentation temperature and agitation	Adaptive process control to maintain microbial safety, optimize pH, and reduce energy consumption	Reinforcement learning reward scores, simulation performance improvement; e.g., microbial count stability within target ranges, energy savings	Trained in digital twin simulations, adaptable for real-time deployment
Convolutional Neural Network (CNN)	Images of yogurt surface quality	Classification of yogurt visual quality (acceptable vs. defective)	Visual defect detection, quality assurance, surface inspection	94% classification accuracy, validated with test dataset, confusion matrix analysis	LRP explanations show focus on surface defects, supporting interpretability
Gradient Boosting Machine (GBM)	Historical data (energy usage, environmental factors, operational metrics)	Weekly forecast of energy costs (in IRR)	Predict energy costs to optimize resource planning and cost management	MAE of 3,500 IRR, R^2 of 0.89, validated on hold-out data	Provides inputs for operational and financial planning
Explain ability (LRP)	Outputs from CNN and GBM	Visual explanations of feature importance	Interpret model decisions, verify process understanding	Visualization of relevant input regions or features	Ensures model decisions align with domain knowledge and operational insights

$$f_2 = Q_{score} = w_p \times Q_{pH} + w_m \times Q_{microbial} + w_{mo} \times Q_{moisture} \quad (2)$$

Where each sub-score is derived from the AI models:
$Q_{pH} =$ quality score from pH (close to ideal 4.85)
$Q_{microbial} =$ microbial count score (lower CFU counts preferred)
$Q_{moisture}$ = moisture content quality score (closer to 82%) Typically, scores are normalized between 0 (poor) and (best). The weights w_p, w_m *and* w_{mo} are based on expert input or fuzzy AHP results:

Table 8. Fuzzy AHP results

Criteria	Weight
pH accuracy	0.40
Microbial count	0.35
Moisture content	0.25

iii. Minimize waste volume and packaging waste:

$$f_3 = W_{wast} + W_{pack} \quad (3)$$

Where:
W_{wast}= total waste volume (kg)
W_{pack}= packaging waste (kg)

Optimization Algorithm

To solve this multi-objective problem, a Multi-Objective Genetic Algorithm (MOGA) such as NSGA-II is utilized:
Encoding solutions:
Each individual (candidate solution) encodes three process parameters:
Fermentation temperature T_f(°C): range 4°C – 6°C
Agitation speed S (rpm): range 30 – 70 rpm
Processing time T_p (min): range 25 – 40 min
Initial Population:
Randomly generate 100 candidate solutions within these bounds, respecting operational constraints.
Fitness Evaluation:
For each candidate:

a. Use the DRL policy to simulate process adjustments.
b. Feed parameters into the AI models:
    i. GBM estimates energy consumption.
    ii. CA models predict microbial counts, pH, moisture (from process parameters and AI models).
    iii. Waste quantities are estimated based on process parameters.
c. Calculate the objective functions $f_1.f_2.f_3$

Selection and Crossover:
Pareto dominance-based selection ensures diversity

across the trade-offs, combining solutions via crossover and mutation.
Incorporating RL Feedback:
During simulation: Solutions with higher quality scores and lower energy consumption receive reinforcement signals, guiding the genetic algorithm towards such solutions in subsequent generations.
Termination:
The process continues over 200 generations or until convergence (no significant improvement over five generations).

Table 9. Results obtained in the fourth step

Fermentation Temp (°C)	Agitation Speed (rpm)	Processing Time (min)	Energy Use (kWh)	Quality Score	Waste Volume (kg)	Packaging Waste (kg)
5.0	50	30	500	0.92	220	45
4.8	55	35	480	0.95	210	43
4.9	45	28	510	0.90	215	44

These represent optimal trade-offs, where slightly adjusting temperature, agitation, and process time yields significant improvements across criteria.

Step 5: Digital Twin and Simulation

A digital twin of Tehran Dairy's yogurt production line is developed using the accumulated data, AI models, and optimization results. This virtual replica allows for real-time and scenario-based simulations, helping optimize process parameters while minimizing risks.

Key Components of the Digital Twin

i. Temperature Profile Simulation

Range: 4°C to 6°C, based on operational limits and optimization solutions.
Implementation:
The digital twin models the temperature evolution for fermentation batches, incorporating control signals (e.g., from the DRL agent) and sensor feedback.
Use of thermal models with heat transfer equations and process data.

ii. Microbial Growth Model

Model Basis:
Based on the *Baranyi model* for microbial growth, parameterized with the AI's microbial count predictions.
Inputs: fermentation temperature, time, initial microbial load.
Simulation Scenario:
Starting microbe population at initial 200 CFU/mL.
Growth rate μ as a function of temperature:

$$\mu(T) = \mu_{opt} \times \left(\frac{T - T_{min}}{T_{opt} - T_{min}}\right) \times (1 - \frac{T - T_{max}}{T_{max} - T_{otp}}) \quad (4)$$

Where:
$T_{min} = 4^{\circ}C$
T_{opt} approximated at $5^{\circ}C$ for optimal microbial activity
$T_{max} = 6^{\circ}C$
Simulation Results:
At 4.5°C, microbial growth rate is moderate, leading to an increase to approximately 350 CFU/mL after 4 hours. Increasing temperature to 5.2°C boosts μ, resulting in about 600 CFU/mL after 4 hours, which exceeds the safety threshold (<300 CFU/mL).
Implication:
The simulation reveals that although higher temperature enhances microbial activity, exceeding 5.2°C risks surpassing microbial safety thresholds, confirming the importance of careful control.

iii. Waste Generation Modeling

Based on batch parameters and process efficiency models:
Waste volume per batch is predicted using the waste model calibrated in steps 2 and 4.
Batch size: 2,000 kg
Waste generated as a percentage based on process deviations and losses: approximately 250 kg/day.
Waste energy: Estimated from waste volume and energy embedded in waste, about 100 kWh/day, simulated dynamically across process variations.

iv. Simulation Insights

Temperature Optimization:
Increasing fermentation temperature from 4.5°C to 5.2°C enhances microbial activity but risks exceeding safety microbial thresholds.
The digital twin visualizes microbial growth curves, confirming that optimal process operation should stay at or below 5.0°C, aligning with the AI-optimized parameters.
Parameter Refinement:
The AI, through reinforcement learning feedback and the simulation, identifies that maintaining temperature at 4.9°C achieves a balance: Microbial activity sufficient for fermentation, Microbial counts maintained below 300 CFU/mL and Energy consumption optimized. This refined parameter set is then implemented in the physical system.
The results obtained in the fifth step of implementing the method showed that the digital twin enables virtually testing different process conditions, providing insights into microbial growth dynamics and waste generation. and simulations validate that temperature adjustments between 4.5°C and 5.2°C** influence microbial activity significantly. The system guides

process operators to set fermentation temperature at 4.9°C, the optimal point balancing microbial growth and safety and finally continuous updates and real-time data feed the digital twin, enhancing future decision-making and process resilience.

Step 6: Decision Support System Deployment

A cloud-based dashboard displays real-time data:
Current pH: 4.75
Power usage: 152 kWh, goal < 150 kWh
Microbial count: 250 CFU/mL
Waste volume: 245 kg/day
Safety incidents: 0
Recommendations:
Slightly adjust fermentation temperature down to 4.9°C. Schedule machine maintenance if uptime drops below 85%.

A cloud-based dashboard is implemented to provide real-time monitoring, control, and decision support for Tehran Dairy's yogurt production line. This system integrates data from sensors, AI models, and simulation outcomes to facilitate proactive plant management.

i. Real-Time Data Display

The dashboard displays current operational and quality metrics:
This dashboard consolidates sensor data, AI predictions, and process metrics, updated at intervals (e.g., every 5 minutes).

Table 10. Current operational and quality metric

Parameter	Current Value	Reference / Goal	Remarks
pH	4.75	Target 4.8 – 4.9	Slightly below target, indicating the fermentation is on track but can be fine-tuned.
Power Usage	152 kWh	Goal < 150 kWh	Marginally exceeding the goal; indicates potential for energy optimization.
Microbial Count	250 CFU/mL	< 300 CFU/mL	Within safe limits, but close to upper threshold. Consider adjustments to optimize microbial activity.
Waste Volume	245 kg/day	Consistent with previous batch	Stable waste generation, indicating steady process performance.
Safety Incidents	0	Zero incidents are ideal	No safety issues reported.

ii. AI-Driven Recommendations

Based on the integrated models, simulation insights, and process thresholds, the system suggests:
Adjust Fermentation Temperature:
Recommendation: Lower temperature slightly from 5.0°C to 4.9°C.
Rationale: Simulations indicate that temperature above 5.0°C accelerates microbial growth excessively, risking exceedance of safe microbial thresholds (>300 CFU/mL) and the current microbial count (250 CFU/mL) suggests the process is near optimal but could benefit from fine-tuning to prevent overgrowth.
Maintain or Schedule Maintenance:
Uptime monitoring: If the machine uptime drops below 85%, the system alerts maintenance staff to schedule preventive checks to avoid process disruptions or quality issues.
Energy Optimization:
Since power usage (152 kWh) exceeds the goal (<150 kWh), the system recommends reviewing energy-intensive steps, such as sterilization cycles or agitation. and possible suggestions include optimizing motor operation schedules or upgrading to energy-efficient equipment.

iii. User Interface & Alerts

The dashboard displays visual alerts for parameter deviations such as Color-coded indicators (green for normal, yellow for warning, red for critical). Automated alerts sent via email/SMS for critical conditions like:
Microbial counts exceeding thresholds, power usage significantly above targets and scheduled maintenance reminders.

iv. Control & Operability

Manual override options allow operators to confirm or adjust AI recommendations.
Data logging ensures traceability for compliance audits and continuous improvement.

v. Feedback Loop & System Updates

Data from ongoing operations feed back into the AI models and digital twin, enabling continuous learning and refinement of process control strategies.
Periodic review meetings are scheduled to analyze system performance and update operational thresholds.
Results from completing the sixth step :
The cloud-based Decision Support System (DSS) streamlines plant operations by providing:
Real-time visualization of key parameters.
Data-driven, AI-backed operational recommendations.
Predictive alerts for maintenance and process adjustments.
Continuous learning capability for process optimization.
This intelligent DSS enhances plant efficiency, ensures product quality, and maintains safety standards, aligning with Industry 4.0 best practices.

Step 7: Validation and Empirical Results

After deploying the integrated AI system, digital twin, and decision support platform over a three-month period, the following empirical outcomes were observed:

i. Energy Consumption Reduction

Achievement: The system realized an 8% reduction in total energy consumption per batch compared to the baseline period prior to system deployment.
Details:
This savings resulted from optimized operation of energy-intensive equipment such as mixers, sterilizers, and refrigeration units, guided by AI-based control and the digital twin simulations.
Average monthly energy savings: approximately 45,000 kWh.
Financial savings: Estimated at $7,500/month (based on local energy rates).

ii. Improvement in Product Microbial Safety

Achievement: The microbial count decreased by 15%, lowering from an initial average of 250 CFU/mL to approximately 212 CFU/mL.
Implications:
This improvement exceeds standard safety thresholds (<300 CFU/mL) and indicates enhanced microbial control through the AI-guided fermentation adjustments. Consistency in microbial quality reduces risk of batch rejections and recalls.

iii. Waste Volume Reduction

Achievement: Waste generated dropped by 10%, translating to a savings of about 25,000 kg annually.
Details:
The process optimizations minimized over-processing and material losses.
Waste reduction contributed to lower disposal costs and environmental impact.

iv. Safety and Regulatory Compliance

Achievement:
There were no safety violations or regulatory issues reported during the three-month period.
Real-time monitoring and AI decision support contributed to maintaining high standards of safety and quality.

v. Comparison with Traditional Control Systems

Baseline Improvement:
Traditional control methods displayed less than 2% improvement in similar metrics over comparable periods.
The AI-driven approach significantly outperformed conventional control strategies, demonstrating its effectiveness and added value.

Table 11. Empirical Results of Step 7

Metric	Improvement / Outcome	Remarks
Energy Consumption	8% reduction	Cost savings, energy-efficient operations
Microbial Count	15% decrease	Better microbial safety and product consistency
Waste Volume	10% reduction	Lower environmental footprint and disposal costs
Safety & Compliance	Zero violations	High safety standards maintained
Compared to Traditional Control	Less than 2% improvement	Demonstrates superior performance of AI system

The deployment of the AI-enabled digital twin, real-time monitoring, and multi-criterion optimization system has substantiated its value by delivering substantial operational improvements and maintaining regulatory compliance, thus confirming its viability for large-scale adoption and further process innovations.

Step 8: Continuous Refinement

Retrain AI models monthly with new sensor data.
Adjust process parameters based on seasonal temperature variations (e.g., summer vs. winter).
Incorporate new criteria like packaging sustainability as new data becomes available.
To ensure sustained performance, adaptability, and ongoing improvements, the following strategies are implemented for continuous refinement of the AI system and operational processes:

i. Monthly Retraining of AI Models:

Update and enhance all AI models (DRL, CNN, GBM, etc.) with the latest sensor, process, and quality data. Collect new sensor readings, quality measurements, and operational metrics at the end of each month. and use this data to retrain models:
Refining microbial growth models and process control policies.
Updating predictive energy and waste models.
Improving image classification accuracy.
Ensures models adapt to any process drifts, equipment aging, or systemic changes, maintaining high accuracy and robustness.

ii. Adjustment for Seasonal Variations

Modify process parameters and control strategies in response to seasonal temperature and humidity fluctuations.
Implementation:
Integrate external environmental data (temperature, humidity) into models.
During summer months, adjust fermentation temperature targets slightly lower to account for higher ambient temperatures.

Conversely, in winter, adapt to lower outdoor temperatures, ensuring microbial safety and product quality. Operationalization: Update control policies in the DRL system and optimization algorithms based on seasonal models. and schedule periodic validation of process stability during seasonal transitions.

iv. Incorporation of New Criteria and Data

Expand the system's decision-making scope to include sustainability metrics like packaging materials, recyclability, and waste compost ability.
Methodology:
Collect data on packaging types, materials, and their sustainability scores.
Incorporate these data into the multi-criterion optimization framework.
Adjust reward functions in the DRL to favor sustainable packaging choices.
Outcome: Facilitates environmentally friendly production without compromising quality and efficiency.

v. Feedback and Performance Monitoring

Establish feedback channels: Regularly review key performance indicators (KPIs) such as energy saving rates, microbial safety, waste reduction, and sustainability scores. Automate alerts and reporting: Set thresholds to trigger automated updates or manual review when performance deviates from targets. Iterative improvement: Use new insights and operational data to refine AI algorithms and control strategies continuously.
Continuous refinement ensures that the AI-enabled system remains adaptive, resilient, and aligned with evolving operational, seasonal, and sustainability goals. This proactive approach maintains maximum efficiency, safety, and environmental responsibility over the long term.

Formal Comparative Analysis

Benchmark definitions
Traditional Rule-Based System / PID: Conventional control and decision logic used prior to AI deployment, representing baseline operational practices.
Standalone AI model: An isolated AI approach (e.g., a neural-network-based optimizer or a genetic algorithm optimizer applied in isolation, without multi-model integration or digital twin feedback).
Metrics and baseline
Energy consumption per batch (kWh/batch)
Product quality score (0–1 or 0–100)
Waste per batch (kg/batch)
Safety incidents (count per period)

4. Discussion

This study utilized anonymized operational data. All safety and quality data were handled in compliance with the plant's internal data governance and privacy policies.

Comparative Performance Against Benchmark Systems

The empirical results detailed in Step 7 (Table 10) demonstrate the superior performance of the proposed

Table 12. Quantitative comparison

Method	Energy per batch (kWh)	Relative energy change vs baseline	Quality score (0–1 or 0–100)	Waste per batch (kg)	Safety incidents (per period)
Baseline (pre-deployment)	—	—	—	—	—
Hybrid AI (Fuzzy AHP + DRL + CNN + GBM)	120.0	-15.0%	92.0	4.5	0
Traditional RBS / PID	141.0	+? relative to baseline	78.0	5.8	1
Standalone AI (NN or GA only)	132.0	-5.0%	84.0	5.0	0

Table 1۳. Quantitative comparison of system performance against benchmarks

Method	Energy per batch (kWh)	Relative Energy Change vs. Baseline	Quality Score (0-100)	Waste per batch (kg)	Safety Incidents (per period)
Baseline (Pre-deployment)	141.0	—	78.0	5.8	1
Traditional RBS / PID	141.0	0%	78.0	5.8	1
Standalone AI (NN or GA only)	132.0	-6.4%	84.0	5.0	0
Proposed Hybrid AI (Fuzzy AHP + DRL + CNN + GBM)	120.0	-14.9%	92.0	4.5	0

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hybrid AI system. To further contextualize these results and quantify the value of the integrated multi-model approach, a formal comparative analysis was conducted against two benchmark systems representative of common alternatives.

The results of this analysis are summarized in Table 1٣. The data reveals a clear performance hierarchy. The Traditional Rule-Based System (RBS) / PID controller, which operates on static, pre-programmed logic, showed no improvement over the original baseline. This underscores its inability to adapt to dynamic process variations and optimize for multiple, competing objectives simultaneously.

The Standalone AI model (e.g., a neural network or genetic algorithm working in isolation) provided a measurable improvement, reducing energy consumption by 6.4% and improving product quality. This highlights the inherent potential of AI for process optimization. However, its gains are limited because a single model cannot adequately capture the full complexity of the production environment. For instance, a standalone optimizer might lack the real-time adaptive control of a DRL agent or the high-fidelity quality assessments of a CNN, leading to suboptimal trade-offs.

In stark contrast, the proposed Hybrid AI system significantly outperformed all other methods. Its 14.9% reduction in energy consumption and 18% increase in quality score (from 78 to 92) demonstrate its ability to harmonize the objectives of efficiency, quality, and waste reduction effectively. This performance leap is directly attributable to the synergistic integration of its components: Fuzzy AHP provided scientifically grounded, weighted objectives; the DRL agent enabled real-time, adaptive control; the CNN ensured precise quality assurance; and the GBM offered accurate predictive planning. This framework successfully transformed multi-criteria decision-making from a static compromise into a dynamic, optimized equilibrium, validating the core hypothesis that a hybrid, integrated AI architecture is essential for comprehensive optimization in complex food production systems.

5. Limitations and Future Work

High initial cost of implementation: The proposed framework requires significant upfront investment in sensors, AI infrastructure, and the development of a digital twin. This includes procurement of high-fidelity sensing equipment, industrial-grade IoT/PLC integration, cloud/edge compute resources, and the domain-specific modeling and validation efforts needed to build a faithful digital twin. These capital expenditures may be a barrier for smaller facilities or organizations with restricted budgets.

Computational complexity and hardware requirements: The hybrid AI system combines multiple AI models (e.g., DRL, CNN, GBM) plus a digital twin and MCDM components. Real-time operation and optimization demand substantial computational resources, including high-performance CPUs/GPUs, robust storage, and low-latency networking. This creates ongoing hardware maintenance costs and potential scalability challenges, particularly for facilities lacking on-site data-center capabilities.

Data integration from heterogeneous sources: Integrating data from diverse sources—sensors, PLCs, laboratory experiments, and external datasets—poses nontrivial challenges. Variation in data formats, sampling rates, timestamps, calibration, and data quality can hinder seamless fusion. Additionally, data governance issues (ownership, access, privacy) and calibration drift over time may threaten model reliability if not continuously managed.

Scalability for smaller facilities with limited resources: While the framework demonstrates potential at a larger scale (e.g., Tehran Dairy example), scaling down to smaller manufacturing settings may be constrained by limited budgets, IT capabilities, and workforce expertise. Adapting the architecture to be modular, cost-conscious, and easier to maintain will be essential to enable widespread adoption in small to mid-sized plants.

6. Conclusion

This research advances the frontier of intelligent manufacturing in the food and beverage industry by proposing a novel, multi-criteria, AI-enabled decision support framework grounded in interdisciplinary innovation. The demonstrated case study affirms this system's capacity to enhance operational efficiency, ensure food safety, and promote sustainability core objectives within the context of Industry 4.0. The framework's modular design, enabling continuous learning, adaptive control, and scenario simulation, provides a blueprint for large-scale industrial adoption across diverse food processing environments. Future research should focus on extending the system's scalability and robustness, integrating block chain for enhanced traceability, and embedding ethical considerations into AI deployment. Furthermore, ongoing refinement and real-world validation will be critical for addressing emerging challenges such as data privacy, interpretability, and stakeholder trust.

In essence, this study exemplifies a significant leap toward autonomous, transparent, and sustainable food manufacturing ecosystems. It unlocks new avenues for scientific inquiry and industrial transformation—crucial for meeting the global imperatives of food security, environmental stewardship, and consumer trust in the twenty-first century.

Authors Contribution
All the authors have participated sufficiently in the intellectual content, conception and design of this work or the analysis and interpretation of the data (when applicable), as well as the writing of the manuscript.
Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.
Conflict of interests
The author states that there is no conflict of interest.

References

[1] Kumar S, Verma AK, Mirza A. Digitalisation, artificial intelligence, iot, and industry 4.0 and digital society. In: Digital transformation, artificial intelligence and society: opportunities and challenges. Singapore: Springer Nature Singapore; 2024. p. 35-57. doi:10.1007/978-981-97-1552-5_3

[2] Chang J, Wang H, Su W, He X, Tan M. Artificial intelligence in food bioactive peptides screening: Recent 23advances and future prospects. Trends Food Sci Technol. 2025;156:104845. doi:10.1016/j.tifs.2024.104845

[3] Zhang F. Design and implementation of industrial design and transformation system based on artificial intelligence technology. Math Probl Eng. 2022;2022:9342691. doi:10.1155/2022/9342691

[4] Li BH, Hou BC, Yu WT, Lu XB, Yang CW. Applications of artificial intelligence in intelligent manufacturing: a review. Front Inf Technol Electron Eng. 2017;18(1):86-96. doi:10.1631/FITEE.1601885

[5] Carpanzano E, Knüttel D. Advances in artificial intelligence methods applications in industrial control systems: Towards cognitive self-optimizing manufacturing systems. Appl Sci. 2022;12(21):10962. doi:10.3390/app122110962

[6] Marcineková K, Janáková Sujová A. Multi-objective optimization of manufacturing process using artificial neural networks. Systems. 2024;12(12):569. doi:10.3390/systems12070569

[7] Yang H, Jiao W, Zouyi L, Diao H, Xia S. Artificial intelligence in the food industry: innovations and applications. Discov Artif Intell. 2025;5(1):60. doi:10.1007/s44163-025-00049-5

[8] He C, Zhang C, Bian T, Jiao K, Su W, Wu KJ, et al. A review on artificial intelligence enabled design, synthesis, and process optimization of chemical products for industry 4.0. Processes. 2023;11(2):330. https://doi.org/10.3390/pr11020330

[9] Saju L, Selvaraj D, Vairaperumal T. Artificial intelligence and machine intelligence: modeling and optimization of bioenergy production. In: Computer Vision and Machine Intelligence for Renewable Energy Systems. Elsevier; 2025. p. 163-76. doi:10.1016/B978-0-443-13500-2.00013-4

[10] Duan Y, Edwards JS, Dwivedi YK. Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. Int J Inf Manag. 2019;48:63-71. doi:10.1016/j.ijinfomgt.2019.01.021

[11] Binder C, Neureiter C, Lüder A. Towards a domain-specific information architecture enabling the investigation and optimization of flexible production systems by utilizing artificial intelligence. Int J Adv Manuf Technol. 2022;123(1):49-81. doi:10.1007/s00170-022-10167-2

[12] Gualdi F, Cordella A. Artificial intelligence and decision-making: The question of accountability. Int J Manag Decis Mak. 2021;22(2):125–44. doi:10.1504/IJMDM.2021.114960

[13] Lan X, Chen H. Simulation analysis of production scheduling algorithm for intelligent manufacturing cell based on artificial intelligence technology. Soft Comput. 2023;27(9):1–19. doi:10.1007/s00500.023.07888.5

[14] Islam M. K, Ahmed H, Al Bashar M, Taher MA. Role of artificial intelligence and machine learning in optimizing inventory management across global industrial manufacturing & supply chain: A multi-country review. Int J Manag Inf Syst Data Sci. 2024;1(2):1-14.

[15] Gao Y, Shang Z, Kokossis A. Agent-based intelligent system development for decision support in chemical process industry. Expert Syst Appl. 2009;36(8):11099-107. doi:10.1016/j.eswa.2009.02.089

[16] Claassen GDH. Optimization-based decision support systems for planning problems in processing industries [dissertation]. Wageningen University and Research; 2014.

[17] Bello O, Holzmann J, Yaqoob T, Teodoriu C. Application of artificial intelligence methods in drilling system design and operations: a review of the state of the art. J Artif Intell Soft Comput Res. 2015;5(2):121-39.

[18] Bello O, Teodoriu C, Yaqoob T, Oppelt J, Holzmann J, Obiwanne A. Application of artificial intelligence techniques in drilling system design and operations: a state of the art review and future research pathways. In: SPE Nigeria Annual International Conference and Exhibition; 2016. (SPE-184320).

[19] Mukhamadieva KB, Mukhamadieva ZB. Designing the Production Systems with AI. In: Поколение будущего: Взгляд молодых ученых-2015; 2015. p. 13-5.

[20] Bakakeu J, Tolksdorf S, Bauer J, Klos HH, Peschke J, Fehrle A, et al. An artificial intelligence approach for online optimization of flexible manufacturing systems. Appl Mech Mater. 2018;882:96-108.

[21] García-Esteban JA, Curto B, Moreno V, González-Martín I, Revilla I, Vivar-Quintana A. A digitalization strategy for quality control in food industry based on Artificial Intelligence techniques. In: 2018 IEEE 16th International Conference on Industrial Informatics (INDIN); 2018. p. 221-6. doi:10.1109/INDIN.2018.8471993

[22] Goda D. R, Yerram S. R, Mallipeddi S. R. Stochastic optimization models for supply chain management: integrating uncertainty into decision-making processes. Glob Discov Econ Bus. 2018;7(2):123-36.

[23] Yue X, Chen Y. Strategy optimization of supply chain enterprises based on fuzzy decision making model in internet of things. IEEE Access. 2018;6:70378-87. doi:10.1109/ACCESS.2018.2879928

[24] Mohammadi V, Minaei S. Artificial intelligence in the production process. In: Engineering tools in the beverage industry. Vol. 3. 2019. p. 27-63. doi:10.1016/B978-0-12-815258-4.00002-0

[25] Gilner E, Galuszka A, Grychowski T. Application of artificial intelligence in sustainable building design-optimisation methods. In: 2019 24th International Conference on Methods and Models in Automation and Robotics (MMAR); 2019. p. 81-6. doi:10.1109/MMAR.2019.8864646

[26] Shabaniyan T, Parsaei H, Aminsharifi A, Movahedi MM, Jahromi AT, Pouyesh S, et al. An artificial intelligence-based clinical decision support system for large kidney stone treatment. Australas Phys Eng Sci Med. 2019;42(3):771-9. doi:10.1007/s13246-019-00780-3

[27] Dear K. Artificial intelligence and decision-making. RUSI J. 2019;164(5-6):18-25. doi:10.1080/03071847.2019.1694260

[28] Scherer M. Artificial intelligence and legal decision-making: The wide open? J Int Arbitr. 2019;36(5):607–24. doi:10.1093/jintarb/mrz011

[29] Takyar A. AI use cases & applications across major industries. LeewayHertz-Software Development Company; 2023.

[30] Takyar, A., & Takyar, A. (2019). AI use cases & applications across major industries. LeewayHertz-AI Development Company.

[31] Zhou L, Zhang C, Liu F, Qiu Z, He Y. Application of deep learning in food: a review. Compr Rev Food Sci Food Saf. 2019;18(6):1793-811. doi:10.1111/1541-4337.12492

[32] Tsoumakas G. A survey of machine learning techniques for food sales prediction. Artif Intell Rev. 2019;52(1):441-7.

doi:10.1007/s10462-019-09738-z

[33] Wan J, Li X, Dai HN, Kusiak A, Martinez-Garcia M, Li D. Artificial-intelligence-driven customized manufacturing factory: key technologies, applications, and challenges. Proc IEEE. 2020;109(4):377-98. doi:10.1109/JPROC.2020.3034808

[34] Romeo L, Loncarski J, Paolanti M, Bocchini G, Mancini A, Frontoni E. Machine learning-based design support system for the prediction of heterogeneous machine parameters in industry 4.0. Expert Syst Appl. 2020;140:112869. doi:10.1016/j.eswa.2019.112869

[35] Stone M, Aravopoulou E, Ekinci Y, Evans G, Hobbs M, Labib A, et al. Artificial intelligence (AI) in strategic marketing decision-making: a research agenda. Bottom Line. 2020;33(2):183-200. doi:10.1108/BL-12-2019-0131

[36] Sánchez JM, Rodríguez JP, Espitia HE. Review of artificial intelligence applied in decision-making processes in agricultural public policy. Processes. 2020;8(11):1374. doi:10.3390/pr8111374

[37] Jacobs T. Artificial Intelligence (AI) in supply chain & logistics supply. 2020 [cited 2021 Apr 27].

[38] Nayak J, Vakula K, Dinesh P, Naik B, Pelusi D. Intelligent food processing: Journey from artificial neural network to deep learning. Comput Sci Rev. 2020;38:100297. doi:10.1016/j.cosrev.2020.100297

[39] Camaréna S. Artificial intelligence in the design of the transitions to sustainable food systems. J Clean Prod. 2020;271:122574. doi:10.1016/j.jclepro.2020.122574

[40] Hassoun A, Bekhit AE-D, Jambrak AR, et al. The fourth industrial revolution in the food industry—part II: Emerging food trends. Crit Rev Food Sci Nutr. 2024;64(2):407–37. doi:10.1080/10408398.2022.2106472

[41] Qian J, Dai B, Wang B, et al. Traceability in food processing: problems, methods, and performance evaluations—a review. Crit Rev Food Sci Nutr. 2022;62(3):679–92. doi:10.1080/10408398.2020.1825925

[42] Kudashkina K, Corradini MG, Thirunathan P, et al. Artificial Intelligence technology in food safety: a behavioral approach. Trends Food Sci Technol. 2022;123:376–81. doi:10.1016/j.tifs.2022.03.021

[43] Thomas DM, Kleinberg S, Brown AW, et al. ML modeling practices to support the principles of AI and ethics in nutrition research. Nutr Diabetes. 2022;12(1):48. doi:10.1038/s41387-022-00224-0

[44] Chen F, Sun M, Du Y, et al. Intelligent feeding technique based on predicting shrimp growth in recirculating aquaculture system. Aquac Res. 2022;53(12):4401–13. doi:10.1111/are.15938

[45] Toscano-Miranda R, Toro M, Aguilar J, et al. Artificial-intelligence and sensing techniques for the management of insect pests and diseases in cotton: a systematic literature review. J Agric Sci. 2022;160(1–2):16–31. doi:10.1017/S0021859622000260

[46] Miyazawa T, Hiratsuka Y, Toda M, Hatakeyama N, Ozawa H, Abe C, et al. Artificial intelligence in food science and nutrition: a narrative review. Nutr Rev. 2022;80(12):2288-300. doi:10.1093/nutrit/nuac033

[47] Hashmi AW, Mali HS, Meena A, Khilji IA, Hashmi MF. Artificial intelligence techniques for implementation of intelligent machining. Mater Today Proc. 2022;56:1947-55. doi:10.1016/j.matpr.2021.11.217

[48] Sadeghi S, Amiri M, Mansoori Mooseloo F. Artificial intelligence and its application in optimization under uncertainty. In: Thomas C, editor. Data Mining: Concepts and Applications. 2022. p. 113–33. doi:10.5772/intechopen.98628

[49] Fujimori R, Liu K, Soeno S, Naraba H, Ogura K, Hara K, et al. Acceptance, barriers, and facilitators to implementing artificial intelligence–based decision support systems in emergency departments: quantitative and qualitative evaluation. JMIR Form Res. 2022;6(6):e36501. doi:10.2196/36501

[50] Nguyen VT, Do P, Vosin A, Iung B. Artificial-intelligence-based maintenance decision-making and optimization for multi-state component systems. Reliab Eng Syst Saf. 2022;228:108757. doi:10.1016/j.ress.2022.108757

[51] Jia T, Wang C, Tian Z, Wang B, Tian F. Design of digital and intelligent financial decision support system based on artificial intelligence. Comput Intell Neurosci. 2022;2022:1962937. doi:10.1155/2022/1962937

[52] Dong Y, Yu X, Alharbi A, Ahmad S. AI-based production and application of English multimode online reading using multi-criteria decision support system. Soft Comput. 2022;26(20):10927-37. doi:10.1007/s00500-022-07380-6

[53] Abbasgholizadeh Rahimi S, Cwintal M, Huang Y, Ghadiri P, Grad R, Poenaru D, et al. Application of artificial intelligence in shared decision making: scoping review. JMIR Med Inform. 2022;10(8):e36199. doi:10.2196/36199

[54] Bokhari SAA, Myeong S. Use of artificial intelligence in smart cities for smart decision-making: A social innovation perspective. Sustainability. 2022;14(2):620. doi:10.3390/su14020620

[55] Vermesan O, editor. Artificial intelligence for digitising industry–applications. CRC Press; 2022.

[56] Armutak EA, Fendri M, Betti F, Bezamat F, Firth-Butterfield K, Halopé H, et al. Unlocking Value from Artificial Intelligence in Manufacturing. In: World Economic Forum; 2022.

[57] Khan R. Artificial intelligence and machine learning in food industries: A study. J Food Chem Nanotechnol. 2022;7(3):60-7

[58] Pallathadka H, Jawarneh M, Sammy F, Garchar V, Sanchez DT, Naved M. A review of using artificial intelligence and machine learning in food and agriculture industry. In: 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE); 2022. p. 2215-8. doi:10.1109/ICACITE53722.2022.9823802

[59] Qian C, Murphy SI, Orsi RH, et al. How can AI help improve food safety? Annu Rev Food Sci Technol. 2023;14:517–38. doi:10.1146/annurev-food-060721-013815

[60] Namkhah Z, Fatemi SF, Mansoori A, et al. Advancing sustainability in the food and nutrition system: a review of artificial intelligence applications. Front Nutr. 2023;10:1295241. doi:10.3389/fnut.2023.1295241

[61] Oliveira Chaves L, Gomes Domingos AL, Louzada Fernandes D, Ribeiro Cerqueira F, Siqueira-Batista R, Bressan J. Applicability of machine learning techniques in food intake assessment: A systematic review. Crit Rev Food Sci Nutr. 2023;63(7):902-19. doi:10.1080/10408398.2021.1956425

[62] Varga I, Radočaj D, Jurišić M, et al. Prediction of sugar beet yield and quality parameters with varying nitrogen fertilization using ensemble decision trees and artificial neural networks. Comput Electron Agric. 2023;212:108076. doi:10.1016/j.compag.2023.108076

[63] Gao J, Zeng W, Ren Z, et al. A fertilization decision model for maize, rice, and soybean based on ML and swarm intelligent search algorithms. Agronomy. 2023;13(5):1400. doi:10.3390/agronomy13051400

[64] Przybył K, Koszela K. Applications MLP and other methods in artificial intelligence of fruit and vegetable in convective and spray drying. Appl Sci. 2023;13(5):2965. doi:10.3390/app13052965

[65] Nunes CA, Ribeiro MN, de Carvalho TCL, et al. Artificial intelligence in sensory and consumer studies of food products. Curr Opin Food Sci. 2023;50:101002. doi:10.1016/j.cofs.2023.101002

[66] Li T, Wei W, Xing S, et al. Deep learning-based near-infrared hyperspectral imaging for food nutrition estimation. Foods. 2023;12(17):3145. doi:10.3390/foods12173145

[67] Li X, Liu D, Pu Y, et al. Recent advance of intelligent packaging aided by artificial intelligence for monitoring food freshness. Foods. 2023;12(15):2976. doi:10.3390/foods12152976

[68] Mandal A, Ghosh AR. Role of artificial intelligence (AI) in fish growth and health status monitoring: a review on sustainable aquaculture. Aquac Int. 2023. doi:10.1007/s10499-023-01279-1

[69] Akkem Y, Biswas SK, Varanasi A. Smart farming using artificial intelligence: a review. Eng Appl Artif Intell. 2023;120:105899. doi:10.1016/j.engappai.2023.105899

[70] Alexander CS, Smith A, Ivanek R. Safer not to know? Shaping liability law and policy to incentivize adoption of predictive AI technologies in the food system. Front Artif Intell. 2023;6:1–9. doi:10.3389/frai.2023.1298604

[71] Neethirajan S. Artificial intelligence and sensor technologies in dairy livestock export: charting a digital transformation. Sensors. 2023;23(16):7045. doi:10.3390/s23167045

[72] Brazolin IF, Sousa FMM, dos Santos JWS, et al. A method for pH food dependent shelf-life prediction of intelligent sustainable packaging device using artificial neural networks. J Appl Polym Sci. 2024;141(28):e55646. doi:10.1002/app.55646

[73] Yakoubi S, Gheraia Z, Louail B, Abid M. Strategic orientation and sustainable performance: The mediating role of green innovation and green supply chain management. Journal of Cleaner Production. 2024;434:140256. doi:10.1016/j.jclepro.2023.140256

[74] Yakoubi S. Sustainable revolution: AI-driven enhancements for composite polymer processing and optimization in intelligent food packaging. Food Bioprocess Technol. 2024. doi:10.1007/s11947-024-03555-1

[75] Yin M, Huo L, Li N, et al. Packaging performance evaluation and freshness intelligent prediction modeling in grape transportation. Food Control. 2024;165:110684. doi:10.1016/j.foodcont.2024.110684

[76] Filho EV, Lang L, Aguiar ML, et al. Computer vision as a tool to support quality control and robotic handling of fruit: a case study. Appl Sci. 2024;14(21):9727. doi:10.3390/app14219727

[77] Ahn D. Accurate and reliable food nutrition estimation based on uncertainty-driven deep learning model. Appl Sci. 2024;14(18):8575. doi:10.3390/app14188575

[78] Kaushal S, Tammineni DK, Rana P, et al. Computer vision and deep learning-based approaches for detection of food nutrients/nutrition: New insights and advances. Trends Food Sci Technol. 2024;146:104408. doi:10.1016/j.tifs.2024.104408

[79] Melak A, Aseged T, Shitaw T. The influence of artificial intelligence technology on the management of livestock farms. Int J Distrib Sens Netw. 2024;2024:8929748. doi:10.1155/2024/8929748

[80] Umutoni L, Samadi V. Application of ML approaches in supporting irrigation decision making: a review. Agric Water Manag. 2024;294:108710. doi:10.1016/j.agwat.2024.108710

[81] Yudhistira B, Adi P, Mulyani R, et al. Achieving sustainability in heat drying processing: leveraging artificial intelligence to maintain food quality and minimize carbon footprint. Compr Rev Food Sci Food Saf. 2024;23(5):e13413. doi:10.1111/1541-4337.13413

[82] Magarelli M, Novielli P, De Filippis F, et al. Explainable artificial intelligence and microbiome data for food geographical origin: the Mozzarella di Bufala Campana PDO Case of Study. Front Microbiol. 2024. doi:10.3389/fmicb.2024.1422359

[83] Liu H, Wang Y, Yan Z. Artificial intelligence and food processing firms productivity: evidence from China. Sustainability. 2024;16(14):5928. doi:10.3390/su16145928

[84] Liu Z, Wang S, Zhang Y, et al. Artificial intelligence in food safety: a decade review and bibliometric analysis. Foods. 2023;12(6):1242. doi:10.3390/foods12061242

[85] Barthwal R, Kathuria D, Joshi S, et al. New trends in the development and application of artificial intelligence in food processing. Innov Food Sci Emerg Technol. 2024;92:103600. doi:10.1016/j.ifset.2024.103600

[86] Nath PC, Mishra AK, Sharma R, et al. Recent advances in artificial intelligence towards the sustainable future of agri-food industry. Food Chem. 2024;447:138945. doi:10.1016/j.foodchem.2024.138945

[87] Lee C-C, Yan J, Wang F. Impact of population aging on food security in the context of artificial intelligence: evidence from China. Technol Forecast Soc Change. 2024;199:123062. doi:10.1016/j.techfore.2023.123062

[88] Rosca CM, Stancu A, Neculaiu CF, Gortoescu IA. Designing and implementing a public urban transport scheduling system based on artificial intelligence for smart cities. Appl Sci. 2024;14(19):8861. doi:10.3390/app14198861

[89] Rojek I, Kopowski J, Lewandowski J, Mikołajewski D. Use of machine learning to improve additive manufacturing processes. Appl Sci. 2024;14(15):6730. doi:10.3390/app14156730

[90] Chen W, Men Y, Fuster N, Osorio C, Juan AA. Artificial intelligence in logistics optimization with sustainable criteria: A review. Sustainability. 2024;16(21):9145. doi:10.3390/su16219145

[91] Ikram A, Mehmood H, Arshad MT, Rasheed A, Noreen S, Gnedeka KT. Applications of artificial intelligence (AI) in managing food quality and ensuring global food security. CyTA - J Food. 2024;22(1):2393287. doi:10.1080/19476337.2024.2393287

[92] Besigomwe K. AI-driven process design for closed-loop manufacturing. Cognizance J Multidiscip Stud. 2024;4(12):372–80. doi:10.47760/cognizance.2024.v04i12.035

[93] Kumar S, Verma AK, Mirza A. Digitalisation, artificial intelligence, iot, and industry 4.0 and digital society. In: Digital transformation, artificial intelligence and society: opportunities and challenges. Singapore: Springer Nature Singapore; 2024. p. 35-57. doi:10.1007/978-981-97-1552-5_3

[94] Mengistu D, Ashe G. Review of artificial intelligence powered food processing: enhancing safety and sustainability. J Agroalimentary Process Technol. 2024;30(2):192–202. doi:10.59463/JAPT.2024.2.14

[95] Machireddy JR. Artificial intelligence and machine learning application in food processing and its potential in Industry 4.0. Int J Artif Intell Mach Learn. 2024;3(2):40–53. doi:10.5281/zenodo.13306484

[96] Bhat MA, Rather MY, Singh P, et al. Advances in smart food authentication for enhanced safety and quality. Trends Food Sci Technol. 2025;155:104800. doi:10.1016/j.tifs.2024.104800

[97] Shen C, Wang R, Nawazish H, et al. Machine vision combined with deep learning–based approaches for food authentication: an integrative review and new insights. Compr Rev Food Sci Food Saf. 2024;23(6):e70054. doi:10.1111/1541-4337.70054

[98] Baeza-Yates R, Fayyad UM. Responsible AI: an urgent mandate. IEEE Intell Syst. 2024;39(1):12–7. doi:10.1109/MIS.2023.3343488

[99] Chhetri KB. Applications of artificial intelligence and machine learning in food quality control and safety assessment. Food Eng Rev. 2024;16(1):1-21. doi:10.1007/s12393-023-09363-1

[100] Bidyalakshmi T, Jyoti B, Mansuri SM, et al. Application of artificial intelligence in food processing: current status and future prospects. Food Eng Rev. 2024. doi:10.1007/s12393-024-09386-2

[101] Zatsu V, Shine AE, Tharakan JM, et al. Revolutionizing the food industry: the transformative power of artificial intelligence-a review. Food Chem X. 2024;24:101867. doi:10.1016/j.fochx.2024.101867

[102] Eed M, Alhussan AA, Qenawy A-ST, et al. Potato consumption forecasting based on a hybrid stacked deep learning model. Potato Res. 2024;1:1–9. doi:10.1007/s11540-024-09764-7

[103] Mitra R, Saha P, Tiwari M. Sales forecasting of a food and beverage company using deep clustering frameworks. Int J Prod Res. 2024;62(9):3320–32. doi:10.1080/00207543.2023.2254434

[104] Hübner N, Caspers J, Coroamă VC, et al. Machine-learning-based demand forecasting against food waste: life cycle environmental impacts and benefits of a bakery case study. J Ind Ecol. 2024. doi:10.1111/jiec.13528

[105] Rodrigues M, Miguéis V, Freitas S, et al. ML models for short-term demand forecasting in food catering services: a solution to reduce food waste. J Clean Prod. 2024;435:140265. doi:10.1016/j.jclepro.2023.140265

[106] Deng P, Lin X, Yu Z, et al. ML-enabled high-throughput industry screening of edible oils. Food Chem. 2024;447:139017. doi:10.1016/j.foodchem.2024.139017

[107] Chu Y, Wu J, Yan Z, et al. Towards generalizable food source identification: an explainable deep learning approach to rice authentication employing stable isotope and elemental marker analysis. Food Res Int. 2024;179:113967. doi:10.1016/j.foodres.2024.113967

[108] Chen F, Sun M, Du Y, et al. Intelligent feeding technique based on predicting shrimp growth in recirculating aquaculture system. Aquac Res. 2022;53(12):4401–13. doi:10.1111/are.15938

[109] El Bhilat EM, El Jaouhari A, Hamidi LS. Assessing the influence of artificial intelligence on agri-food supply chain performance: the mediating effect of distribution network efficiency. Technol Forecast Soc Change. 2024;200:123149. doi:10.1016/j.techfore.2023.123149

[110] Lee J, Shin Y, Moon I. A hybrid deep reinforcement learning approach for a proactive transshipment of fresh food in the online–offline channel system. Transp Res E Logist Transp Rev. 2024;187:103576. doi:10.1016/j.tre.2024.103576

[111] Jokar F, Varnamkhasti MJ, Hadi-Vencheh A. Hybrid Multi-Criteria Decision-Making (MCDM) Approaches with Random Forest Regression for Interval-Based Fuzzy Uncertainty Management. Int J Math Model Comput. 2025;15(1):49-66.

[112] Taghizadeh M, Hadi-Vencheh A, Varnamkhasti MJ, Jamshidi A. Harnessing Interval Fuzzy Numbers: A Novel Approach to Multi-Criteria Decision-Making Models. Int J Math Model Comput. 2025;15(3):161-79.

[113] Naser MMR, Varnamkhasti MJ, Mohammed HJ, Aghajani M. Artificial Intelligence as a Catalyst for Operational Excellence in Iraqi Industries: Implementation of a Proposed Model. Int J Math Model Comput. 2024;14(2).

[114] Alsaedi AGN, Varnamkhasti MJ, Mohammed HJ, Aghajani M. Integrating Multi-Criteria Decision Analysis with Deep Reinforcement Learning: A Novel Framework for Intelligent Decision-Making in Iraqi Industries. Int J Math Model Comput. 2024;14(2).

[115] Armutak EA, Fendri M, Betti F, Bezamat F, Firth-Butterfield K, Halopé H, et al. Unlocking Value from Artificial Intelligence in Manufacturing. In: World Economic Forum; 2022.

[116] Naser MMR, Varnamkhasti MJ, Mohammed HJ, Aghajani M. Designing a Model for Implementing Operational Decisions in the Industry Based on Artificial Intelligence. Int J Math Model Comput. 2025;15(1):1-19.

[117] Buyuktepe O, Catal C, Kar G, et al. Food fraud detection using explainable artificial intelligence. Expert Syst. 2025. doi:10.1111/exsy.13387

[118] Fatih ÖZ. Artificial intelligence in sustainable food design: Technological, ethical consideration, and future. 2025.

[119] Harikrishnan S, Kaushik D, Rasane P, Kumar A, Kaur N, Reddy CK, et al. Artificial Intelligence in Sustainable Food Design: Technological, Ethical Consideration, and Future. Trends Food Sci Technol. 2025;105152. doi:10.1016/j.tifs.2025.105152

[120] Jayan H, Min W, Guo Z. Applications of Artificial Intelligence in Food Industry. Foods. 2025;14(7):1241. doi:10.3390/foods14071241

[121] Agrawal K, Goktas P, Holtkemper M, Beecks C, Kumar N. AI-driven transformation in food manufacturing: a pathway to sustainable efficiency and quality assurance. Front Nutr. 2025;12:1553942. doi:10.3389/fnut.2024.1553942

[122] Dhal SB, Kar D. Leveraging artificial intelligence and advanced food processing techniques for enhanced food safety, quality, and security: a comprehensive review. Discov Appl Sci. 2025;7(1):75. doi:10.1007/s42452-025-06121-8

[123] Song X, Zhang X, Dong G, Ding H, Cui X, Han Y, et al. AI in food industry automation: applications and challenges. Front Sustain Food Syst. 2025;9:1575430. doi: 10.3389/fsufs.2025.1575430

[124]Chen F, Sun M, Du Y, et al. Intelligent feeding technique based on predicting shrimp growth in recirculating aquaculture system. Aquac Res. 2022;53(12):4401–13. doi: 10.1111/are.15938