



Review

Artificial intelligence for plant-based meat alternatives: Pathways to a sustainable future

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ABSTRACT

The global shift toward sustainable food systems has accelerated the development of plant-based meat alternatives (PBMA), which offer substantial environmental and ethical benefits compared to conventional meat. However, the industry continues to face critical challenges in formulation, processing, texture, sensory evaluation, and consumer acceptance. Traditional trial-and-error approaches are resource-intensive, requiring repeated experimentation, high material consumption, and extended development time. In this context, artificial intelligence (AI) has emerged as a transformative tool for PBMA innovation. This review provides a comprehensive, application-oriented overview of AI methodologies in PBMA, including machine learning, hybrid mechanistic-statistical models, computer-aided molecular design, and advanced data analytics. These approaches are examined in relation to PBMA-specific challenges, such as complex ingredient interactions, multiphase structuring, and sensory optimization. AI applications in process optimization (e.g., extrusion and 3D printing), textural evaluation, and sensory prediction are critically discussed, highlighting both capabilities and limitations. Additionally, we discuss how AI-driven approaches can optimize nutritional profiles and model nutrient bioavailability, thereby enabling the targeted design of functional foods with enhanced health benefits. Furthermore, AI's role in consumer science, including sensory evaluation, acceptance modeling, sentiment analysis, and market prediction, is discussed as a pathway to improving consumer satisfaction and reducing food neophobia. Finally, future research directions are proposed, with emphasis on developing open-access multi-modal databases, integrating AI with omics technologies, and advancing AI-enabled sustainability assessments. By bridging food science with computational intelligence, AI has the potential to accelerate PBMA development, enhance product quality, and promote broader consumer adoption, contributing to a more sustainable food system.

1. Introduction

The global population is expected to increase by nearly 2 billion people over the next 25 years, from the current 8 billion to 9.7 billion in 2050, posing serious challenges to food security and environmental sustainability (Hadidi et al., 2023; Tripathi et al., 2019). On the other hand, traditional livestock farming is increasingly criticized for its substantial negative environmental footprint, contributing to deforestation, greenhouse gas emissions, water depletion, and biodiversity loss.

In contrast, plant-based meat production uses 77% less water and 93% less land, while reducing greenhouse gas emissions by up to 90% (Bryant, 2022; Kustar & Patino-Echeverri, 2021). Consequently, plant-based meat alternatives (PBMA) have gained increasing attention as sustainable substitutes for animal-derived meat, with global production projected to reach 25 million metric tons by 2030 (Li et al., 2023). Despite this rapid growth, several critical challenges must be addressed to support their wider adoption and long-term impact.

One of the primary obstacles in developing PBMA lies in the

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formulation stage, particularly in blending different ingredients to achieve a product that closely mimics the structure, taste, and sensory attributes of animal muscle tissue (Kumari et al., 2023). The complexity of plant proteins, which vary widely in their functional properties, such as solubility, emulsification, gelation, and water-binding capacity, makes it difficult to achieve the desired texture and mouthfeel of real meat (Kyriakopoulou et al., 2021; Tarahi et al., 2024). Besides, previous studies have shown that consumers often find the taste of PBMA to be less appealing than traditional meat, with issues such as dryness, beany odors, and bitter aftertastes, posing significant barriers to their purchase intentions and willingness to pay (Giezenaar et al., 2024). Traditional methods of formulation often rely on trial-and-error, which can be time-consuming and may not yield optimal results. Additionally, the polymer blending law, a key principle in material science, presents additional challenges when applied to food systems, especially in predicting how different materials will interact during processing (Bühler et al., 2022; Kircali Ata et al., 2023). On the other hand, plant-based alternatives often require the addition of various thickening, water-binding, and texture-enhancing agents to simulate meat-like qualities, which can raise concerns about nutrition, food safety, and clean labeling (Ahmad et al., 2022; Sha & Xiong, 2020). These limitations highlight the need for more sophisticated tools to aid in developing plant-based meat products in a simpler, faster, and more efficient way for their widespread applications in everyday dietary intake.

In the last few years, artificial intelligence (AI) has revolutionized the food industry, and its promising benefits are increasingly evident in the development of novel PBMA (Tachie et al., 2023). AI-driven systems, particularly machine learning (ML) models, have become essential tools for optimizing product development and ensuring consistent quality (Saha et al., 2025; Todhunter et al., 2024). These models can predict the behavior of food ingredients, allowing for the formulation of plant-based meat products that closely mimic the texture and taste of traditional meat, which is crucial for consumer acceptance. Furthermore, AI enables consistent quality control across different production batches, ensuring that every product meets the desired sensory attributes (Kircali Ata et al., 2023; McClements et al., 2021b). In this respect, AI technologies can be employed to analyze vast datasets to identify patterns that may not be evident through traditional methods. For instance, AI models can predict optimal extrusion conditions for plant-based proteins, leading to reduced energy consumption and a lower carbon footprint (Pavani et al., 2024; Yudhistira et al., 2024). This not only enhances the sustainability of PBMA but also contributes to cost savings and improved efficiency in the production process. The predictive capabilities of AI, particularly through artificial neural networks (ANNs) and genetic algorithms (GAs), are also driving innovation in various sectors of the food industry (Bedoya et al., 2022). Emerging AI tools are now being applied in nutritional science to optimize nutrient profiles and model nutrient bioavailability, thus facilitating the development of functional foods tailored to specific health objectives (Zhao et al., 2025). In the context of PBMA, these models can forecast the outcomes of different ingredient combinations and processing techniques, enabling rapid prototyping and production. This predictive approach reduces the need for extensive trial-and-error experiments, saving time, resources, and reducing waste (Ding et al., 2023; Mavani et al., 2022). Additionally, AI can assist in the marketing of PBMA by analyzing large-scale data and identifying patterns related to consumer purchasing behavior and willingness to pay, enabling companies to tailor their marketing strategies more effectively (Alam et al., 2024; Ma & Sun, 2020).

Overall, this literature review aims to explore the potential role of AI in addressing the challenges associated with the development of PBMA. Specifically, it critically assesses how diverse AI approaches are applied across major domains, including formulation design, process optimization, textural and sensory evaluation, nutritional profiling, and consumer acceptance. By highlighting both the capabilities and limitations of current AI methodologies, this review provides a structured understanding of their practical relevance and outlines future directions for

integrating AI into sustainable PBMA innovation.

2. Overview of AI technologies

2.1. Basic concepts of AI

AI is broadly defined as the science and engineering of creating machines or systems capable of performing tasks that typically require human intelligence. Since its emergence in the 1950s, AI has evolved considerably. Early developments emphasized symbolic approaches, where computers manipulated explicit rules and symbols. Over time, however, these were gradually replaced by data-driven methods capable of learning directly from large datasets. This transition has been accelerated by advances in computational power, data storage, and algorithmic design, allowing AI to progress from simple logical problem-solving to a transformative technology with applications across health-care, finance, education, industry, and beyond (Boulif et al., 2023; Storey et al., 2025).

At the heart of AI lies ML, which allows systems to improve performance by identifying patterns in data rather than depending solely on explicit programming (Fig. 1). ML is typically divided into three main paradigms. Supervised learning uses labeled data to train models for tasks such as classification and regression. Unsupervised learning identifies patterns and hidden structures in unlabeled datasets through techniques like clustering and dimensionality reduction. Reinforcement learning (RL), a third paradigm, enables an agent to learn decision-making strategies through trial-and-error interactions with its environment, guided by rewards and penalties (Morales & Escalante, 2022). RL has achieved remarkable success in applications such as robotics, resource optimization, and advanced game-playing systems (Ng & Tan, 2025).

A major advancement within ML is deep learning (DL), which employs multilayered ANNs inspired by the human brain. DL systems can automatically extract complex features from raw data, driving major breakthroughs in computer vision, natural language processing, and speech recognition. Unlike earlier algorithms such as support vector machines (SVMs) or naïve Bayes classifiers, which often plateau in performance, DL models typically improve as the volume of data increases, making them especially effective in data-rich environments (Yu et al., 2025).

Recent years have also seen the rise of hybrid architectures, which combine different neural network types to model complex sequential or temporal patterns more effectively (Yu et al., 2025). In parallel, advances in natural language processing (NLP) have enabled machines to interpret, process, and generate human language with unprecedented fluency (Bidyakshmi et al., 2025). Taken together, these developments demonstrate how AI has advanced from a theoretical concept to a versatile toolkit capable of addressing complex challenges across diverse domains.

More recently, advances in DL have culminated in generative AI and large language models (LLMs), which extend transformer architectures from pattern recognition to flexible text generation, code synthesis, and multimodal reasoning. These models are typically pre-trained on massive corpora and then specialized through instruction tuning and reinforcement learning from human feedback (RLHF), often implemented with Proximal Policy Optimization (PPO) to align model outputs with expert preferences and safety constraints. In parallel, tool use and retrieval-augmented generation (RAG) connect LLMs to external resources, such as databases, search engines, simulators, or knowledge graphs, so that responses are grounded in up-to-date, domain-specific information rather than memorized text alone. Together, these training and deployment paradigms enable LLMs to be adapted as “foundation models” for food science, where they can read and synthesize literature, interface with nutrient and recipe databases, and support decision-making across safety, nutrition, and product design (Ma et al., 2024).

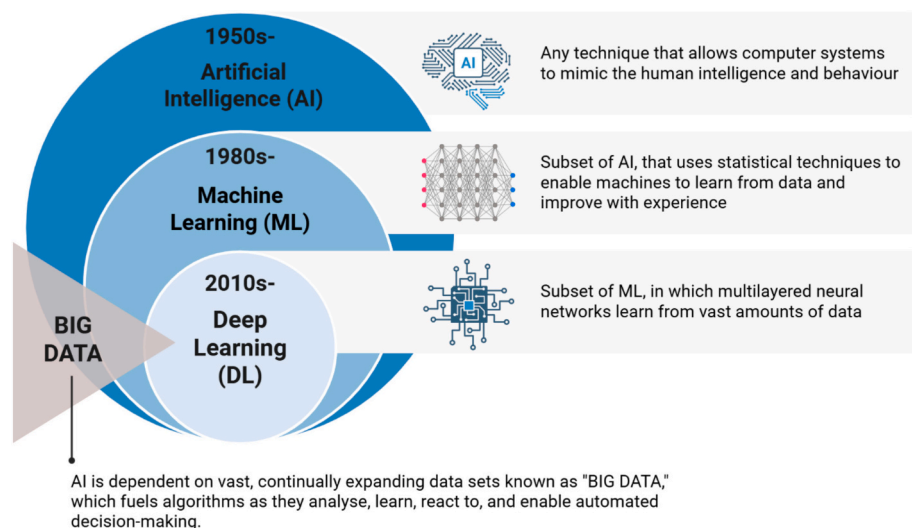


Fig. 1. Conceptual hierarchy of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL). The foundation of these approaches relies on continuously expanding “BIG DATA,” which fuels algorithm development, learning, and automated decision-making.

2.2. History of AI in the food industry

The history of AI in the food industry is closely tied to the broader development of both analytical chemistry and computational sciences (Fig. 2). Early food analysis in the 1930s relied on methods such as gas chromatography, thin-layer chromatography, and pH meters, which laid the foundation for objective assessment of food composition and quality. By the 1940s–1970s, more advanced techniques, e.g., enzyme assays, mass spectrometry, and electrophoresis, emerged, creating a rich database of nutritional and compositional parameters that later became essential inputs for AI-driven models (Miyazawa et al., 2022).

In parallel, AI as a scientific field was born in the mid-20th century. Notably, McCulloch and Pitts (1943) introduced a neural model of computation, and Rosenblatt (1958) developed the perceptron, the first practical pattern recognition system. Through the 1960s and 1970s, natural language programs such as STUDENT and debates on perceptrons shaped the theoretical boundaries of ML models (Bobrow, 1964; Minsky & Papert, 1969). Progress accelerated in the late 1980s and 1990s with backpropagation algorithms, support vector machines, and recurrent neural networks, allowing dynamic modeling of time-series data, particularly relevant for food processing and storage studies (LeCun et al., 1989; Li & Du, 2017). The resurgence of neural networks

in the 2000s, with Hinton's DL frameworks, and the landmark successes of systems such as AlphaGo in 2015, brought AI into mainstream application across industries (Hinton, 2007; Silver et al., 2016). These foundational developments are critical for understanding the evolution of modern AI methodologies now applied in food systems, including PBMA, where complex, multi-parameter interactions require advanced predictive and optimization capabilities.

The food sector began embracing AI meaningfully in the late 2010s, when advances in DL converged with big data from nutrition studies, metabolomics, and food chemistry. AI was applied to nutritional epidemiology (e.g., dietary pattern analysis and foodborne illness detection) (Sadilek et al., 2018; Zhang et al., 2018), food toxicity and allergenicity assessment (IZSTO et al., 2017; Wang et al., 2021), and personalized nutrition strategies (Tsolakidis et al., 2024). ML models demonstrated the ability to predict individual responses to diet, body weight, and metabolic outcomes, outperforming conventional statistical tools (Ramya et al., 2019). Moreover, AI has supported food authentication, quality control, sensory analysis, and supply-chain safety monitoring. By 2020, initiatives such as the AI Dietrofi Subcommittee of the International Life Sciences Institute Japan (ILSI Japan) sought to build predictive models linking multimolecular food intake to human health outcomes, reflecting the growing vision of AI as a driver of

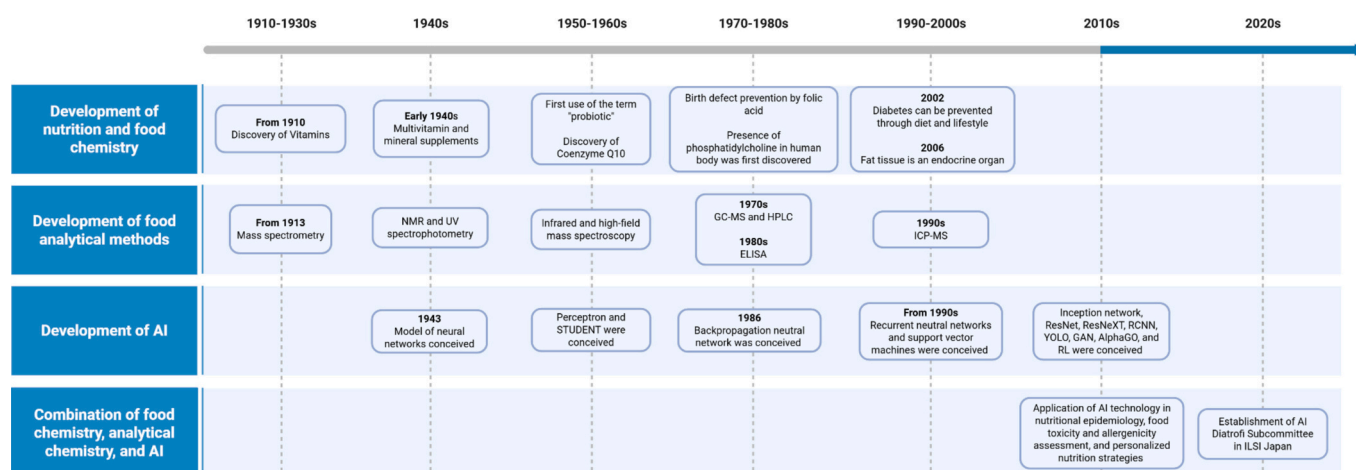


Fig. 2. Timeline of key milestones in the development of AI in food science, highlighting the parallel progress of nutrition and food chemistry, food analytical methods, and AI; adapted from Miyazawa et al. (2022).

next-generation functional foods and precision nutrition (Miyazawa et al., 2022).

Today, AI in the food industry represents the culmination of decades of progress, moving from theoretical neural models to real-world applications in food safety, personalized diets, and sustainable product development. Since 2023, a new “generative wave” has reshaped this historical trajectory, driven by LLMs and multimodal foundation models that can ingest, reason over, and generate food-related knowledge at scale. These systems build on generic models such as GPT-5 and LLaMA-3, but are increasingly adapted to food science via domain-specific instruction datasets, RLHF pipelines, and retrieval-augmented generation over culinary, regulatory, and nutritional corpora (Ma et al., 2024). In food science, LLMs are now being explored for tasks ranging from food safety risk prediction and regulatory compliance to automated recipe development, consumer feedback mining, and nutritional counseling, indicating a shift from narrow task-specific models toward unified language-centric interfaces for the food system.

In parallel, several domain-specialized LLMs have been introduced that illustrate how generative models can be tailored to food knowledge. FoodSky is a Chinese food-oriented LLM trained on the large-scale FoodEarth corpus and enhanced with topic-aware retrieval mechanisms; it demonstrates expert-level performance on the Chinese National Chef and Dietetic examinations and is designed to support culinary creativity and dietetic guidance across diverse user groups (Zhou et al., 2025). FoodGPT, developed for the on-demand food delivery domain, combines supervised fine-tuning with Direct Preference Optimization and PPO-based reinforcement post-training on the FoodInstruct dataset, yielding a domain-specific LLM that outperforms general models on tasks such as product understanding, query tagging, and relevance estimation and has been deployed at scale in industry (Wang et al., 2025). Complementing these text-centric systems, recent studies have also evaluated vision-language models (e.g., ChatGPT, Gemini, Claude, and open-source VLMs) for dietary assessment from food images, showing high accuracy for simple single-item meals but persistent challenges in fine-grained cooking-style recognition and complex mixed dishes (Romero-Tapiador et al., 2025). Despite their considerable potential, these models remain susceptible to hallucinations, citation inaccuracies, and data provenance errors, which may lead to incorrect formulation recommendations or misleading food safety interpretations if used without proper validation. Therefore, outputs generated by LLMs

should be treated as decision-support tools rather than authoritative sources and should be verified by domain experts, particularly in food formulation and safety contexts. Together, these developments mark the beginning of a generative, LLM-driven era in food computing that underpins many of the applications discussed in later sections of this review.

2.3. Potential applications of AI in PBMA

AI has emerged as a powerful data-driven approach for addressing the multifaceted challenges associated with PBMA. Given the inherent complexity of these systems, involving interactions among ingredients, processing conditions, and sensory attributes, conventional empirical methods are often insufficient. In contrast, AI enables the integration and analysis of large, heterogeneous datasets to uncover hidden relationships and predict system behavior with greater accuracy. This capability facilitates the rational design and optimization of PBMA across multiple stages, including formulation, processing, quality evaluation, and consumer analysis (Table 1). By reducing reliance on extensive experimental trials, AI-driven approaches can accelerate product development, enhance consistency, and support more efficient resource utilization.

At the formulation level, AI facilitates the rational design of ingredient combinations by predicting interactions among plant proteins, polysaccharides, lipids, and additives. ML models can identify optimal blends that achieve targeted physicochemical and sensory properties, such as texture, juiciness, and flavor, while also meeting nutritional requirements. In processing, AI plays a key role in optimizing technologies such as extrusion and 3D printing, where multiple parameters (e.g., temperature, moisture, shear rate, and pressure) interact to determine final product structure. AI models, including ANNs and Bayesian optimization (BO), can efficiently explore this multidimensional space, reducing experimental effort and improving product consistency. AI also contributes to quality evaluation by predicting textural and sensory attributes using compositional, rheological, and structural data. DL and computer vision approaches enable non-destructive assessment of structure and appearance, supporting real-time quality control. In addition, AI supports nutritional optimization by enabling multi-objective formulation strategies that balance protein quality, micro-nutrient content, sodium reduction, and bioavailability. Furthermore,

Table 1
Overview of AI techniques and their applications in PBMA.

Application area	AI techniques	Typical inputs	Key outputs	Potential PBMA applications	References
Formulation design	Hybrid ML, GA, and OptCAMD	Ingredient composition and functional properties	Optimal formulations and predicted texture/sensory scores	Protein blending, fat replacement, and texture optimization	(Boukouvala & Floudas, 2017; Eason & Biegler, 2018; Liu et al., 2019; Trystram, 2012; Zhang et al., 2019)
Process optimization	ANN, BO, and GA	Temperature, moisture, shear rate, and pressure	Optimal processing conditions and reduced energy use	Extrusion optimization and HME parameter tuning	(Gulzar et al., 2025a; Jiang et al., 2025; Jung et al., 2023; Shihani et al., 2006)
3D printing and structuring	ML and DL	Rheological data and printing parameters	Printability prediction and structural stability	Food ink design, shape retention, and fiber structuring	(Lu et al., 2023; Ma et al., 2021)
Texture prediction	ML and DL (XGBoost and ANN)	Proximate composition, moisture, and rheology	Hardness, chewiness, and springiness	Reducing trial-and-error in texture design	(Chitra Devi et al., 2025; Giri et al., 2025)
Sensory evaluation	ANN, NLP, SVM, and computer vision	Images, sensory data, and consumer feedback	Sensory prediction and preference mapping	Flavor/appearance prediction and acceptance modeling	(Addanki et al., 2022; Sun et al., 2018)
Consumer behavior and marketing	NLP and ML	Reviews, social media, and purchase data	Sentiment analysis and preference trends	Reducing food neophobia and targeted marketing	(Álvarez-Pato et al., 2020; Chen et al., 2021; Khilji et al., 2021)
Nutritional optimization	ML and multi-objective optimization	Nutrient composition and ingredient database	Optimized nutrient profiles and bioavailability prediction	Protein quality improvement and micronutrient fortification	(Doherty et al., 2021; Westerman et al., 2020; Youn et al., 2024)
Quality control	DL and computer vision	Imaging and structural data	Defect detection and consistency monitoring	Real-time monitoring of PBMA products	(Mayr et al., 2016)

Abbreviations: AI, artificial intelligence; PBMA, plant-based meat alternatives; ML, machine learning; DL, deep learning; ANN, artificial neural network; GA, genetic algorithm; BO, Bayesian optimization; NLP, natural language processing; HME, high-moisture extrusion; XGBoost, eXtreme gradient boosting; SVM, support vector machine; OptCAMD, optimization-based computer-aided molecular design.

NLP and data analytics tools provide valuable insights into consumer preferences, enabling targeted product development and improved market acceptance. Collectively, these applications demonstrate the broad potential of AI in PBMA development. In the following sections, these domains are discussed in detail, highlighting recent advances, practical implementations, and remaining challenges.

3. AI in product formulation and design

Currently, new food products are often developed through trial-and-error to meet specific targets for food characteristics, aiming to satisfy consumer preferences, particularly in terms of sensory attributes. However, this iterative approach is often costly, time-consuming, and environmentally unsustainable (Garcia-Garcia et al., 2021). Consequently, there is an urgent need for more efficient and effective methodologies to accelerate food product design. AI-driven approaches have emerged as promising solutions for addressing these challenges (Nayak et al., 2020). Over the past two decades, the Process Systems Engineering (PSE) community has made significant strides in product design methodologies. However, only limited efforts have been directed toward food product applications (Dubbelboer et al., 2015; Ng et al., 2006). Despite this, considerable efforts have been made to develop mechanistic models and statistical methods to link food characteristics with processing conditions (Asselman et al., 2007; Bower, 2013; Hu, 2017; Shihani et al., 2006). Yet, predicting consumer satisfaction remains a persistent challenge due to the subjective and complex nature of sensory perception. The following sections will discuss two promising computational design methodologies with potential for adaptation to the design of PBMA.

3.1. Hybrid ML and mechanistic modeling approaches

The hybrid ML and mechanistic modeling approach represents a

systematic framework for food product design (Fig. 3). This approach leverages mechanistic models, rooted in physical and chemical principles, to estimate food characteristics and ML models to predict sensorial satisfaction. By integrating these techniques, food product design is formulated as a gray-box optimization problem. The proposed framework incorporates a knowledge base, databases, heuristics, and screening experiments to identify potential ingredient candidates and key operating conditions as design variables. Food quality, represented by sensorial ratings, serves as the objective function and is predicted using a black-box ML model (F) trained on historical data (Boukouvala & Floudas, 2017; Eason & Biegler, 2018). Mechanistic models define design constraints for food characteristics, which are incorporated into the optimization process as penalty functions. GA is then employed to maximize the objective function (i.e., food quality) while satisfying the mechanistic constraints. Following each GA iteration, the optimal solution undergoes experimental validation. During this phase, design constraints are tested, and sensory evaluations are conducted to gather panelists' feedback and verify the predicted ratings. If the constraints are not met or the sensorial ratings deviate from expectations, the experimental data is added to the training set, and the process iterates. The GA-based optimization and experimental iterations continue until the final optimal product is achieved, balancing computational efficiency with empirical validation (Trystram, 2012; Zhang et al., 2019).

The mathematical formulation of this hybrid approach is outlined in Eqs. (1–5). The optimization problem is expressed in Eq. (1), where the objective function seeks to maximize sensorial quality (q) while incorporating penalty functions ($P(Z)$) to ensure physicochemical and processing constraints are satisfied. Eq. (2) represents the mechanistic component, where food characteristics (Z) are computed as a function of ingredient composition (x) and processing conditions (pd). These characteristics are restricted by lower and upper bounds (Z^L and Z^U), as formalized in the penalty function (Eq. (3)). If all constraints are satisfied, $P(Z) = 0$; otherwise, a large negative value ($-M$) is introduced,

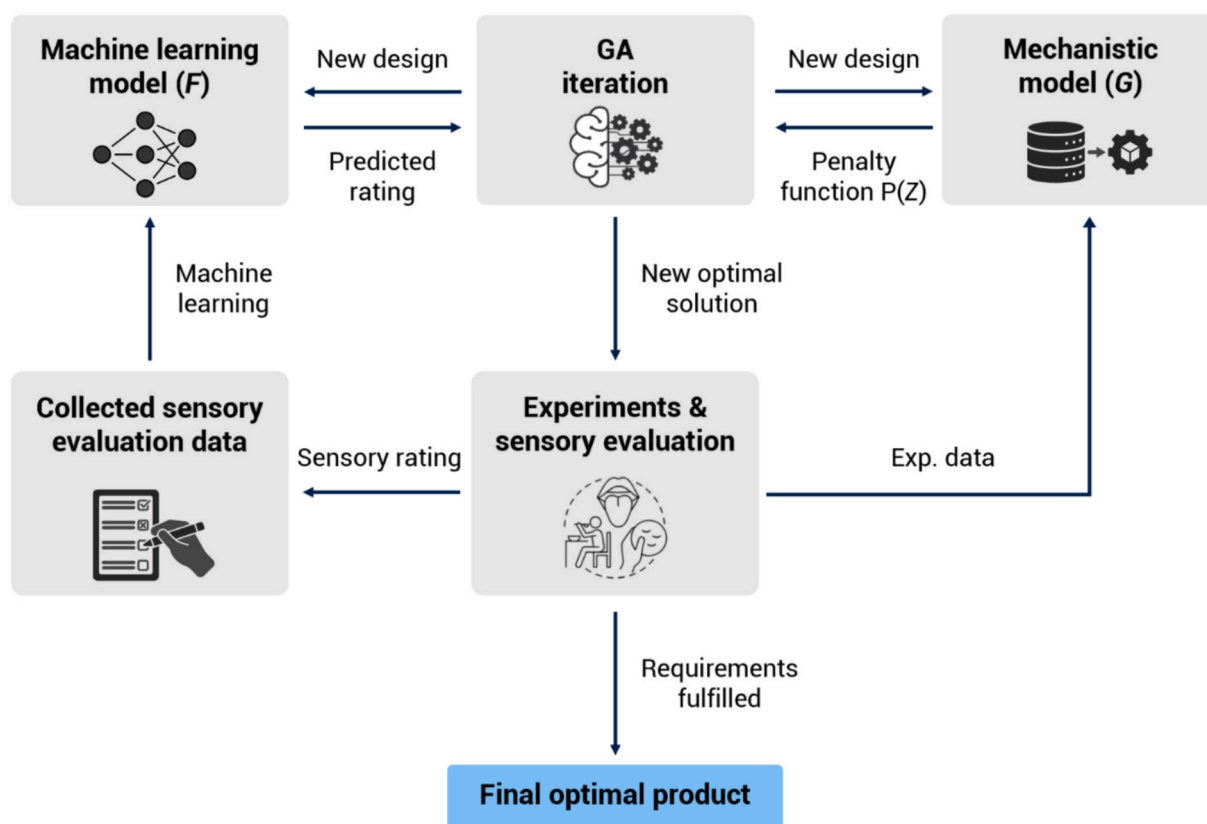


Fig. 3. GA-based solution strategy for solving the gray-box food product design problem; adapted from Zhang et al. (2019).

thereby discouraging infeasible solutions. Eq. (4) incorporates ML models, which are used to predict sensorial scores (q) from the design variables (x and pd) in situations where direct physicochemical modeling of consumer perception is not feasible. Finally, Eq. (5) defines the permissible ranges (c^L and c^U) for the design variables, such as ingredient proportions or processing parameters, to ensure practical and safe product formulations (Zhang et al., 2019). Together, these equations establish a hybrid framework in which mechanistic models capture the physicochemical behavior of the system, ML models account for sensorial responses, and optimization ensures the best possible formulation and processing strategy within feasible design boundaries.

$$\max q + P(Z) \text{ (objective function)} \quad (1)$$

$$Z = G(x, pd) \text{ (mechanistic model)} \quad (2)$$

$$P(Z) = \begin{cases} 0 & \text{if } Z^L \leq Z \leq Z^U \\ -M & \text{otherwise} \end{cases} \text{ (penalty function)} \quad (3)$$

$$q = F(x, pd) \text{ (machine learning model)} \quad (4)$$

$$c^L \leq x, pd \leq c^U \text{ (bounds)} \quad (5)$$

Although this hybrid modeling framework has not yet been directly applied to the design of PBMA, it can be specifically adapted to address the unique complexities of plant-based systems. In PBMA, the design variables (x and pd) may represent protein source selection (e.g., pea, soy, or wheat gluten), protein–polysaccharide ratios, moisture content, and extrusion parameters such as temperature, shear rate, and screw speed. Mechanistic models can be extended to capture PBMA-specific phenomena, including protein denaturation, phase separation, water distribution, and fibrous structure formation during high-moisture extrusion. At the same time, ML models can be trained to predict key quality attributes such as texture (e.g., hardness, chewiness, anisotropy), juiciness, and sensory acceptability based on formulation and processing conditions. Furthermore, this framework is particularly well-suited for PBMA due to the inherently multi-objective nature of their design, where trade-offs must be balanced between texture, flavor, nutritional quality, and processability. By integrating mechanistic understanding

with data-driven prediction, hybrid models can reduce the experimental search space and provide more efficient pathways for optimizing complex, multiphase food systems. Nevertheless, further research is required to develop PBMA-specific datasets, improve model generalizability across different protein systems, and validate these approaches under industrial processing conditions.

3.2. OptCAMD framework

In addition to the hybrid ML and mechanistic modeling framework, other systematic approaches have been developed for product formulation. The computer-aided molecular-mixture design (CAMD) method includes the formation of possible chemical structures, estimation of their physicochemical characteristics, and ultimately selecting appropriate molecules or mixtures with the desired functionality. These properties can be obtained from experimental data or reliable predictive resources. However, given the vast number of potential molecules and functions, selecting the optimum structure is challenging. To address this, an optimization model, OptCAMD, has been established. In OptCAMD, an objective function is defined to screen for the most suitable molecules or mixtures, which may involve maximizing or minimizing a target property or optimizing overall process performance (Alshehri et al., 2025). Notably, Liu et al. (2019) introduced a framework for designing molecular and mixture products that meet specific property targets. This framework incorporates a three-step workflow: (I) preliminary design, (II) CAMD, and (III) product evaluation and verification (Fig. 4). Central to this workflow is the OptCAMD toolbox, an optimization-based platform that combines molecular property prediction with algorithmic search to generate, screen, and refine candidate products. When applied to nine published design problems, OptCAMD successfully replicated reported solutions and, in several cases, identified superior alternatives, highlighting its robustness, efficiency, and broad applicability. In the preliminary step, product characteristics are collected and converted into desired physicochemical properties for the formulation of CAMD problems. In the CAMD step, a mathematical optimization model, Mixed-Integer Linear/Non-Linear programming (MILP/MINLP), is formulated based on structure and feature constraints to create possible mixtures with optimum ingredient candidates (Eq.

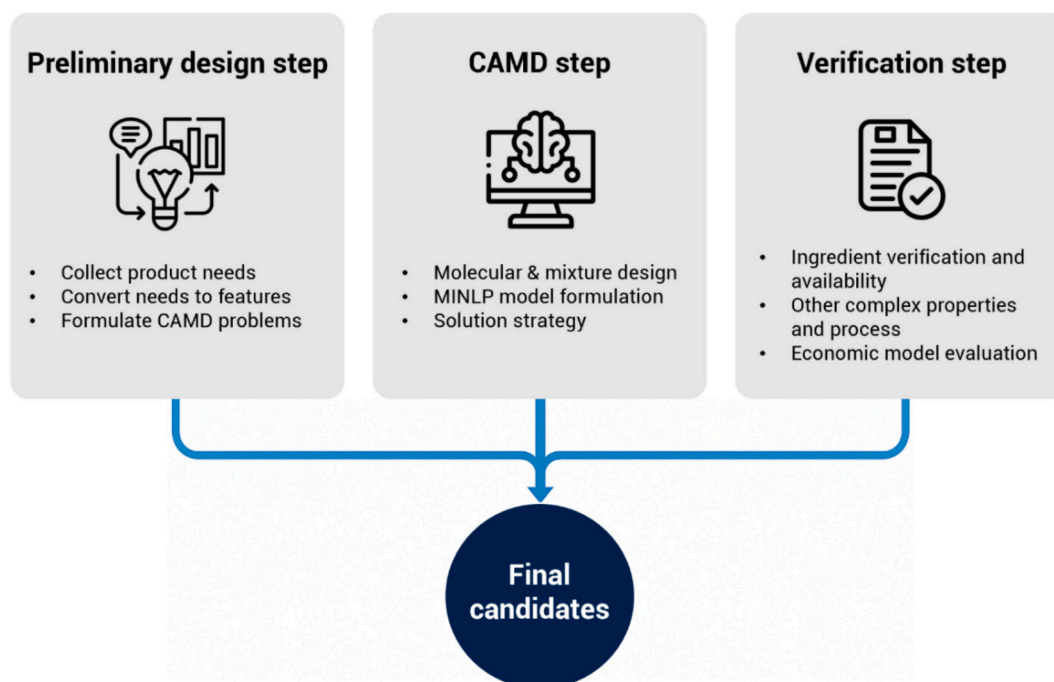


Fig. 4. Flowchart of OptCAMD for mixture product design; adapted from Liu et al. (2019).

(6)). Constraints are lower and upper bounds for the number of components permitted in the mixture, mole fraction of components, and logical constraints such as consumer requirements. Then, a solution is proposed for solving the MILP/MINLP model.

$$M^L \leq \sum_m Y_m \leq M^U, \sum_m X_m = 1 \quad (6)$$

Where:

- Y_m : binary variable indicating selection of ingredient m
- M^L, M^U : lower and upper bounds of the number in the mixture
- X_m : mole fraction of ingredient m

If m is selected: $Y_m = 1$ and $0 < X_m \leq 1$; otherwise, $Y_m = X_m = 0$.

This process generates a list of candidate molecular compositions or mixtures, from which the optimum solution is identified. The shortlisted candidates are subsequently evaluated for efficiency and verified against mixture properties, as well as technological and economic criteria. The OptCAMD framework has proven effective in both replicating established designs and discovering superior product candidates. Although initially developed for chemical-based products, the OptCAMD toolbox shows strong potential for application in the design of food-formulated and functional products. Nevertheless, further research is required to tailor this approach specifically for PBMA.

3.3. AI-assisted polymer blending law

Rheology is the study of the flow and deformation of matter under the influence of applied forces. It is crucial for understanding how materials behave when subjected to shear stress and strain, which is particularly essential in the development of PBMA to mimic the texture, mouthfeel, and structural integrity of traditional meat products (Ahmad & Benjamin, 2023; Eirich, 2012). Rheological properties, measured using instruments such as rotational and capillary rheometers, allow for the analysis of flow behavior, viscosity, and structural changes in plant-based food ingredients under various conditions (Nnyigide & Hyun, 2023). Rotational rheometers are ideal for low-shear applications, while capillary rheometers excel in high-shear scenarios like extrusion, accurately measuring apparent viscosity and flow behavior with necessary corrections (McClements, 2023; McClements et al., 2021b). This understanding of rheological properties aids in the design and optimization of processing techniques for plant-based meat products.

The rheological behavior of food soft matter systems depends on multiple factors that operate across different length scales, from molecular composition to processing conditions. Viscosity and flow behavior fundamentally differ between Newtonian and non-Newtonian food systems, with these differences directly linked to underlying structural attributes and shear rate dependencies. Advanced methodologies such as nonlinear viscoelasticity analysis (e.g., large amplitude oscillatory shear (LAOS)) have revealed microstructural transitions that directly affect sensory perception in processed model foods, establishing quantitative relationships between rheological signatures and consumer experience (Pawde & Dave, 2025). Blends of plant proteins, when subjected to shear and heat, form the structural basis for meat analogs. However, accurately characterizing the properties of these biopolymer blends during the texturizing process presents significant challenges. The complexity arises from the difficulty in obtaining accurate data on the behavior of individual phases within the blend during processing, as these phases interact dynamically and undergo transformations under varying conditions such as heat, shear, and pressure. To address these challenges, the polymer blending law offers a valuable theoretical framework for understanding and predicting the rheological behavior of blends based on the properties of their individual phases. The general form of the polymer blending law is expressed as (Eq. (7)) (Kasapis & Tay, 2009):

$$M^n = \phi_x M_x^n + \phi_y M_y^n \quad (7)$$

Here, M_x and M_y represent the moduli of the two polymers x and y in the blend, and M represents the modulus of the blend. ϕ_x and ϕ_y are the volume fractions of phase x and y , respectively. The parameter n depends on the spatial distribution of the phases and their moduli. When $n = 1$, the blend behaves in an isostrain regime, where the denser continuous phase and the weaker dispersed phase deform equally under stress. In contrast, when $n = 0$, the system adopts an isostress behavior, where the weaker continuous phase limits the stress on the more viscous dispersed phase, resulting in a uniform stress distribution across the blend. For systems with two continuous phases, the blend behaves in a bi-continuous regime with $n = 0.2$, where the moduli of the individual phases determine the overall modulus of the blend (Kasapis, 2008; Schreuders et al., 2020).

In blends where both phases contain water and biopolymers, rheological behavior also depends on water distribution, which can be assessed using the solvent avidity parameter (p). Schreuders et al. (2020) explored this concept by applying the polymer blending law to fibrous blends of pea protein isolate (PPI) and soy protein isolate (SPI) with wheat gluten (WG). Using time-domain nuclear magnetic resonance (TD-NMR), they investigated water distribution within individual phases and the overall blends. The study revealed that the n -value changed with processing conditions, reflecting shifts in the blend's morphology. Specifically, PPI-WG blends shifted toward an isostrain regime at higher temperatures and longer processing times, while SPI-WG blends exhibited intermediate or bi-continuous behavior under similar conditions. These findings demonstrate the potential of the n -value to elucidate morphological changes and fibrous structure development in plant protein blends under different processing conditions.

Despite its usefulness, applying the polymer blending law in PBMA production is often labor-intensive, time-consuming, and costly due to the trial-and-error nature of experimentation. Integrating AI into this process has significant potential to streamline it by predicting rheological behavior, optimizing formulations, and simulating phase interactions, thus reducing the need for extensive experimentation. However, research on this application of AI is still limited. Future PBMA studies could couple polymer-blending-law parameters (e.g., fitted n and solvent avidity p) with neural-network constitutive models to create differentiable, data-efficient surrogates for extrusion-induced structuring, enabling true inverse design of fibrous textures (St. Pierre et al., 2024). On the other hand, translating these optimized formulations into structured meat analogs ultimately depends on precise control of processing conditions. Therefore, the following section focuses on the role of AI in optimizing key processing technologies used in PBMA production.

4. AI in process optimization

Process optimization is a critical step in the production of PBMA, where achieving the desired texture, structure, and sensory quality often depends on fine-tuning complex parameters such as temperature, moisture, shear, and ingredient composition. Traditional optimization methods are often labor-intensive, time-consuming, and limited in scope. AI, however, offers a transformative alternative by enabling the modeling, prediction, and optimization of multiple interdependent variables simultaneously. This allows manufacturers to design more efficient processing strategies, minimize variability, and develop consistent, high-quality products that closely mimic the structural and sensory attributes of conventional meat.

4.1. Extrusion processing

In the extrusion process, a common technique used for the production of PBMA, the raw materials, particularly protein and starch, are

transformed into the final product by applying heat, pressure, and mechanical shear (Singh et al., 2021). The process occurs within an extruder, which can be divided into four main zones: feeding, mixing, melting, and cooling (Fig. 5A). As the raw materials progress through the extruder, the temperature is increased significantly in the melting zone, often reaching between 150 and 170 °C. This high temperature causes a sharp rise in pressure, leading to the plastification, or melting, of the ingredients (Schmid et al., 2022). During this stage, the proteins lose their native three-dimensional (3D) structure due to the breakdown of heat-labile non-covalent linkages and covalent disulfide bonds, enhancing their mobility (Verbeek & Van Den Berg, 2010). After that, the thermodynamic incompatibility between protein and other components, e.g., starch, leads to phase separation into continuous and dispersed phases. The continuous phase typically consists of the more soluble components while the dispersed phase includes the less soluble or insoluble proteins and other ingredients. This phase separation is crucial for forming the final product's structure, especially in the production of fibrous meat analogs (Zhang et al., 2022). However, several challenges may arise during phase separation, particularly in controlling the viscosity of the extrudate. Viscosity plays a key role in phase separation, as lower viscosity allows better mobility of molecules, facilitating the formation of distinct phases. For instance, high moisture content (40–70%) typically reduces extrudate viscosity, allowing for easier flow of material through the extruder. However, at very high water contents (> 70%), the extrudate becomes too soft due to the significantly lower protein concentration (Chen et al., 2011; Rehrah et al., 2009; Vatansever et al., 2020). Another challenge is managing temperature gradients within the extruder. The complex geometry of extruder screws creates non-uniform thermal stresses, leading to variations in viscosity along the extruder's length (Emin & Schuchmann, 2017). Therefore, temperature control is critical, as too high or too low temperatures can either inhibit proper phase separation or lead to undesirable textures (Zhang et al., 2022). Additionally, shear stress, influenced by screw configuration and speed, remarkably affects the material's texture and phase distribution (McClements & Grossmann, 2021; Sengar et al., 2023). High shear can cause depolymerization of macromolecules, while low shear may not provide sufficient mechanical energy for desired structural transformations (Schmid et al., 2022). Thus, achieving the desired fibrous structure is one of the biggest challenges for manufacturers. This is where AI comes in, offering advanced capabilities for predicting and optimizing the rheological behaviors of materials during the PBMA production process.

As above-mentioned, proteins undergo phase separation during the extrusion, and thereby, achieving the right balance is crucial for mimicking the fibrous texture of the real meat. AI can model these thermal effects, helping to predict the phase behavior of proteins and other ingredients and guide the selection of optimal processing temperatures (Jung et al., 2023). In extrusion processing, where plant-based materials are subjected to high shear forces and varying temperatures, AI algorithms can optimize conditions for producing a consistent product with the desired techno-functional and sensory characteristics (Alasi et al., 2024; Vishwakarma et al., 2023). For instance, in wheat flour and wheat-black soybean blends, ANNs outperformed traditional response surface methodology (RSM) models in predicting extrusion parameters such as specific mechanical energy, expansion ratio, water absorption index, water solubility index, and sensory characteristics (e.g., crispness, hardness, appearance, and overall acceptability). These findings underscore the ANN's superior ability to describe the extrusion process and optimize the quality of extruded products under varying conditions of temperature, moisture, and screw speed (Shihani et al., 2006). Similarly, Lee et al. (2024) demonstrated that AI, particularly ML algorithms such as random forest and multilayer perceptron (MLP), can predict the viscosity of common hydrocolloids in plant-based meat industry (i.e., xanthan gum, locust bean gum, guar gum, methylcellulose, konjac, and sodium alginate) under varying conditions of temperature, concentration, and shear rate. In this respect, the MLP model, with

hyperparameters tuned through BO, outperformed traditional rheological models, achieving superior prediction accuracy ($R^2 \approx 0.99$). Importantly, AI-generated viscosity predictions aligned closely with observed textural attributes of plant-based meats, underscoring their potential to replace labor-intensive empirical testing with rapid, data-driven insights.

High-moisture extrusion (HME) has been widely investigated as a promising technique for producing fibrous plant-based meat analogs, and recent studies have integrated AI to optimize this process. For example, one study explored the effects of sorbitol on the textural properties of soy protein concentrate-based high-moisture meat analogs using a combined AI and GA framework (Fig. 5B). This approach enabled simultaneous adjustment of multiple parameters, replicating chicken- and beef-like textures while capturing complex non-linear interactions between sorbitol levels, moisture content, and extrusion conditions. Texture profile analysis (TPA) revealed that hardness decreased sharply from 3893 ± 308 g at 0% sorbitol to 421 ± 54 g at 20%, while cooking yield and water absorption capacity increased with sorbitol addition, accompanied by microstructural and protein conformational changes observed via SEM and FTIR. In contrast, oil absorption capacity decreased as sorbitol levels rose, demonstrating the trade-offs in techno-functional properties (Jiang et al., 2025). In another study, BO approach was compared with RSM for optimizing HME conditions, including barrel temperature, water content, and cooling die temperature (Fig. 5C). By varying extrusion condition, BO converged on optimal tensile strength and mechanical properties using only 10–11 trials, compared to 15 trials for RSM, and achieved significantly lower prediction error ($\leq 24.5\%$ vs. up to 61.0%) (Gulzar et al., 2025a). A further study investigated the incorporation of tannic acid (TA) into soy protein concentrate-based high-moisture meat analogs (SPC-HMMA), using AI-based optimization to tailor texture and cooking quality. By modeling the complex interactions between TA concentration and moisture content, AI effectively identified optimal conditions that replicated the texture of animal meat. Specifically, AI pinpointed 0.3% TA with 63.5% moisture as optimal for chicken-like analogs, and 1.45% TA with 59.3% moisture for beef-like analogs. This data-driven approach eliminated the need for extensive trial-and-error testing, providing a precise strategy for balancing improvements in hardness, chewiness, and fibrous structure while avoiding overly dense textures (Gulzar et al., 2025b). While AI has significantly improved the prediction and optimization of extrusion parameters, challenges remain in scaling these models to industrial conditions, where variability in raw materials and process instability can reduce prediction accuracy.

4.2. 3D printing

In recent years, the role of AI has become even more crucial in advanced technologies, e.g., 3D printing, which is increasingly being used to produce PBMA. In this process, materials are extruded layer-by-layer to form complex structures that mimic meat's muscle fibers. The success of 3D printing depends heavily on controlling the rheological properties of the plant-based inks used in the process (Caron et al., 2024; Tarahi, 2024). These inks need to have the right viscosity and flow behavior to be extruded through the printer without losing shape, while also being firm enough to hold their structure after printing. AI models can predict how plant-based inks will behave during extrusion and printing, allowing for better control over the shape, texture, and appearance of the final product (Chen et al., 2023; Lee et al., 2020; Outrequin et al., 2024; Padhiary et al., 2024). The 3D food printing workflow begins with a digital file designed in computer-aided design (CAD) software, where the model can be precisely optimized before being exported as an .stl file. Specialized slicing software then translates the digital model into G-code, defining layer thickness, printing speed, nozzle temperature, and platform settings. AI can assist in optimizing these parameters by linking them to material rheology and printability constraints, enabling adaptive adjustment of printing conditions during

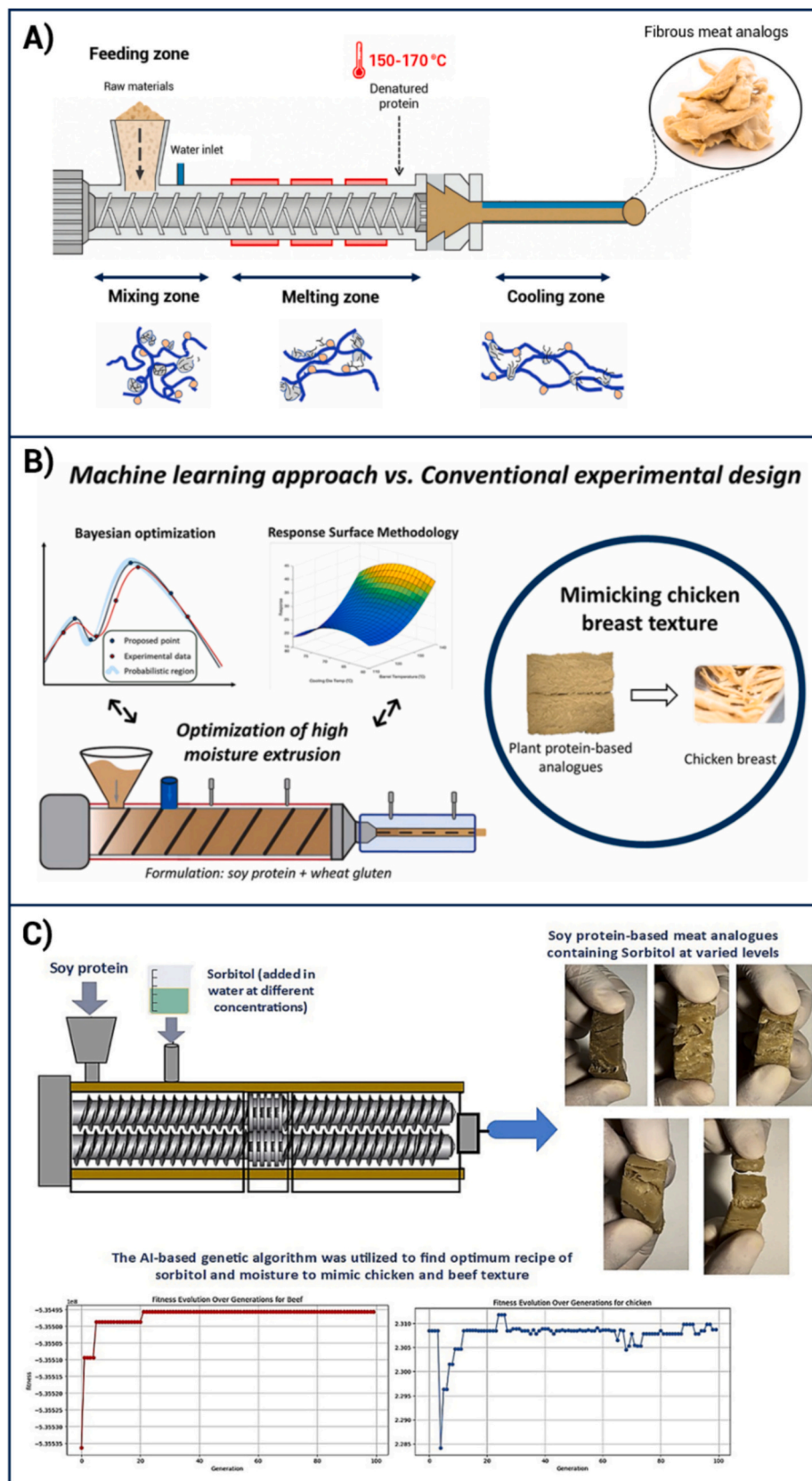


Fig. 5. AI-assisted optimization of high-moisture extrusion (HME) for the formation of fibrous meat analogs. (A) Schematic of the twin-screw extrusion process, illustrating the feeding, mixing, melting, and cooling zones that transform plant proteins into fibrous structures. (B) Application of Bayesian optimization (BO) compared with Response Surface Methodology (RSM) for optimizing soy protein–wheat gluten formulations, showing AI's superior ability to predict and replicate chicken breast texture (Jiang et al., 2025). (C) Integration of sorbitol at different concentrations into soy protein-based formulations and optimization using AI-based genetic algorithms (GAs) to replicate chicken- and beef-like textures (Gulzar et al., 2025a).

processing (Aghababaei et al., 2025). This robotics-driven system enables decentralized and highly customizable food production, with AI integrating real-time image data and sensor feedback to ensure printability and extrudability of complex food materials (Fig. 6A) (Ma et al., 2021).

Despite the growing demand and interest in 3D printing for food manufacturing, predicting the printability of food-grade materials based on biopolymer composition and rheological properties remains a significant challenge. A recent study addressed this issue by developing two image-based printability assessment metrics, printed filaments' width and roughness, and applying them to evaluate the printability of hydrogel-based food inks using RSM, regression analysis, and ML. In this work, hydrogel inks formulated from low-methoxyl pectin and cellulose nanocrystals with varying ionic crosslinking densities were tested (Fig. 6B). RSM and linear regression provided good predictability of rheological properties based on formulation parameters but failed to predict the printability metrics. To overcome this, random forest classifiers were trained on rheological and compositional data to predict filament width, roughness, and overall printability. Remarkably, models trained only on rheological measurements achieved high prediction

accuracies, 82% for width and roughness labels and 88% for overall printability, highlighting the potential of ML to reliably predict the printability of polysaccharide-based inks and possibly extend to food inks of different compositions (Lu et al., 2023). Moreover, AI is invaluable for correlating rheological properties with sensory attributes like texture, mouthfeel, and chewiness, which are critical factors in consumer acceptance of plant-based meat products (Oyinboba, 2023; Salmenkallio-Marttila et al., 2004). By analyzing large datasets that include both rheological and sensory data, AI can identify patterns and relationships that would be difficult to detect using traditional methods (Ahmad & Benjamin, 2023). ML models can even be trained to predict sensory outcomes based on rheological data, reducing the need for costly and time-consuming sensory panels (Yang et al., 2023). In a recent study, Outrequin et al. (2024) showed that the rheological parameters of plant-based inks can be accurately predicted and standardized using ML techniques, with the Extra Trees Regressor model achieving high predictive accuracy ($R^2 = 0.98$ for training and 0.94 for testing). This integration of experimental insights and predictive modeling enables the fine-tuning of viscoelastic properties, ensuring the production of food products with precise dimensions and enhanced structural integrity,

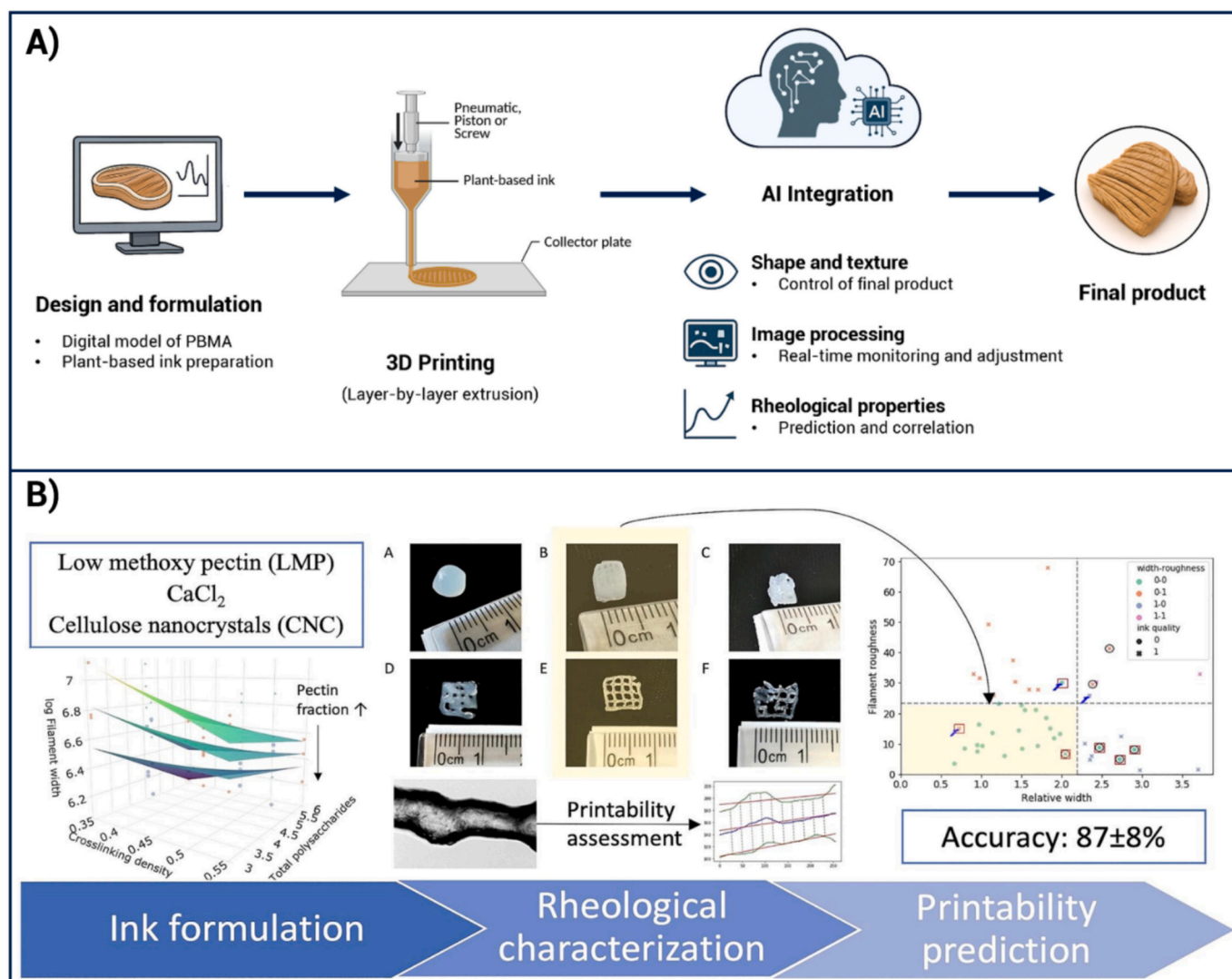


Fig. 6. AI-assisted 3D printing process for the production of food-grade materials. (A) Workflow of AI-integrated 3D printing, where digital PBMA models and plant-based inks are processed via layer-by-layer extrusion, with AI optimizing shape, texture, and extrudability through real-time monitoring and rheological prediction. (B) Printability prediction of hydrogel-based inks composed of low-methoxyl pectin and cellulose nanocrystals using image-based metrics (filament width and roughness), RSM, and ML, with a nozzle moving speed of 6 mm/s. Random forest models trained on rheological data achieved high accuracies (82% for width/roughness; 88% overall), highlighting AI's potential to generalize printability prediction across food-ink formulations (Lu et al., 2023).

advancing the field of 3D food printing.

Beyond production optimization, AI applications can also extend to personalized nutrition, where it facilitates the development of tailored products for specific dietary needs and preferences. For example,

personalized 3D-printed foods have been developed for military personnel, older adults with chewing difficulties, and ethnic populations, utilizing ancestral ingredients such as quinoa, amaranth, and kaniwa to create high-protein and nutrient-rich food products (Bedoya

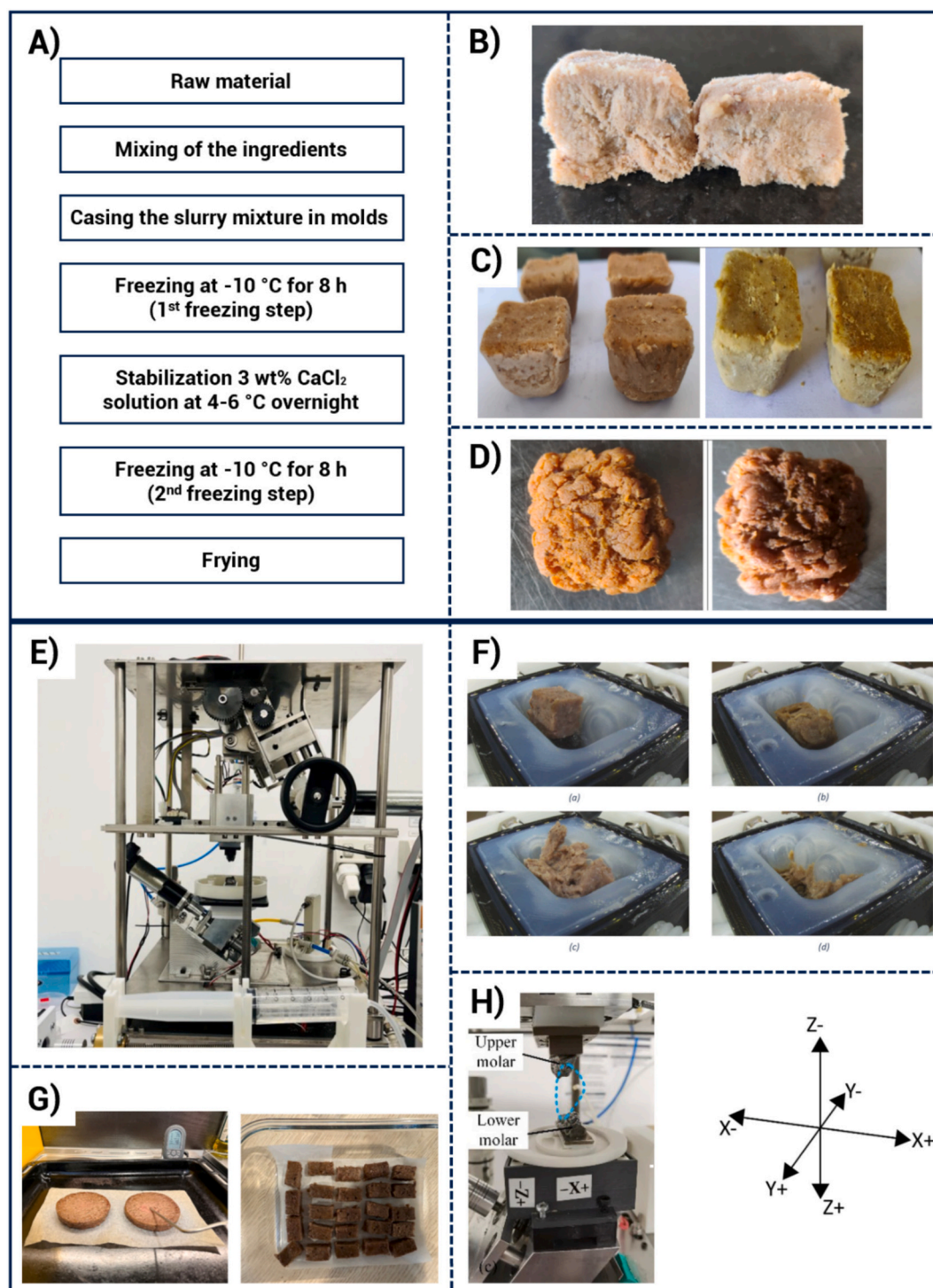


Fig. 7. Development and evaluation of plant-based meat analogs using freeze structuring and multimodal mastication datasets. (A) Schematic process of freeze structuring for legume-based meat analogs, including raw material blending, molding, controlled freezing, CaCl_2 stabilization, and frying. (B) Cut sectional view of the optimized sample showing the visible fibrous structure formed through freeze structuring. (C) Experimental trial images of meat substitutes with increased levels of pea protein isolate (PPI, left) and soy protein isolate (SPI, right), demonstrating formulation-dependent variations in structure. (D) Optimized deep-fried meat substitute sample produced under freeze structuring and mixture design optimization (Chitra Devi et al., 2025). (E) Biomimetic chewing robot (ChewBot) with a soft robotic oral cavity simulating human mastication. (F) Sequential images of beef and plant-based patties undergoing robotic chewing cycles, highlighting bolus breakdown and oral processing behavior. (G) Preparation of cooked beef and plant-based patties, standardized into 2 g samples for in vivo and in vitro mastication tests. (H) Load cell measurement of chewing force vectors (X, Y, Z axes) used to capture dynamic mastication profiles (Akrawita et al., 2025).

et al., 2022; Prasad et al., 2025). This enables manufacturers to fine-tune their formulations, ensuring that the final product not only looks like meat but also has the desired mouthfeel and eating experience. In conclusion, AI plays a key role in advancing 3D printing for PBMA by optimizing rheological properties, enhancing sensory attributes, and enabling personalized nutrition solutions. Its integration into this technology ensures the development of tailored PBMA that meet both consumer preferences and nutritional needs.

5. AI in evaluation of textural properties

Characterizing the textural properties of meat analogs is crucial for developing products that mimic the sensory attributes of meat, such as cutting resistance and mouthfeel (e.g., bite strength). These properties are typically evaluated using TPA, also known as the “double compression test,” which involves compressing and relaxing the sample twice between parallel plates at a defined speed. This method is designed to replicate a twofold chewing motion (McClements et al., 2021a; Nishinari et al., 2019) and has been widely applied for evaluating the texture of meat analogs (Mattice & Marangoni, 2020; Samard & Ryu, 2019). During testing, the sample is compressed to a relative deformation, and the force required for compression and relaxation is measured. The TPA yields key textural parameters, including hardness, resilience, springiness, and chewiness (calculated as hardness $\times$ cohesiveness $\times$ springiness) (McClements et al., 2021a).

Plant-based meat represents a viable solution, but for consumer acceptance, it must deliver comparable texture, crunchiness, flavor, and juiciness to real meat. Achieving this typically requires numerous iterative experiments and domain expertise to optimize formulations and processes (Jang & Lee, 2024). To address this, ML approaches have been applied to analyze food texture more efficiently by taking various ingredient attributes (e.g., fat, fiber, protein, and moisture) as inputs. In one study, ML algorithms such as Naïve Bayes, Random Forest, XGBoost, K-Nearest Neighbors (KNN), and Decision Tree were applied to predict key textural attributes of PBMA. The models focused on parameters such as chewiness and hardness, achieving notable predictive performance with mean absolute percentage error (MAPE) values of 19% and 12% and root mean square error (RMSE) values of 8.9% and 5.98% for hardness and chewiness, respectively. These results demonstrate the capacity of ML methods to streamline PBMA development by predicting consumer-relevant textural attributes with reduced trial-and-error experimentation (Giri et al., 2025). In another study, PPI, SPI, and vital wheat gluten (VWG) have been combined with other structuring agents to produce fibrous, meat-like textures (Fig. 7A-D). A mixture design approach coupled with freeze structuring was employed to optimize formulations, with ML models integrated to predict textural and sensory properties. The optimized formulation, containing 18.9% PPI, 12.6% SPI, and 8.5% VWG, exhibited a hardness of 815.587 N, springiness of 0.845 mm, overall acceptability of 8.7, and water activity of 0.887. Importantly, the ML predictions closely matched experimental results, with Gradient Boosting achieving the best prediction for hardness (RMSE = 24.698, R^2 = 0.986), AdaBoost performing best for springiness (RMSE = 0.019, R^2 = 0.940) and overall acceptability (RMSE = 0.284, R^2 = 0.904), and XGBoost achieving the highest accuracy for water activity (RMSE = 0.002, R^2 = 0.985). This integration of mixture design with ML highlights how dimensionality reduction and data-driven modeling can improve formulation efficiency and product quality while reducing experimental burden (Chitra Devi et al., 2025). Building on these approaches, further research has employed ML models with built-in feature selection mechanisms to predict textural properties of PBMA. In this approach, the proximate compositions of raw materials, i.e., protein, fat, carbohydrate, fiber, ash, and moisture, along with targeted moisture contents of the final analogs, were introduced as input features to ML models. Algorithms such as Ridge, XGBoost, and MLP, with built-in feature selection mechanisms, were employed to predict key texture parameters, specifically hardness and chewiness. The

models achieved an MAPE of 22.9% and an RMSE of 10.101 for hardness, and a MAPE of 14.5% with an RMSE of 6.035 for chewiness. Among the tested features, carbohydrates, fat, and targeted moisture content emerged as the most critical factors influencing textural properties. The study further examined multicollinearity among the features, model linearity, and inconsistencies in food compositions to validate the robustness of the framework (Kircali Ata et al., 2023). These findings highlight that ML is a powerful tool for formulating PBMA, providing a data-driven route to optimize product development cycles, reduce costs, and accelerate market readiness.

Building on these developments, recent research has explored advanced optimization frameworks that combine predictive modeling with adaptive experimental design. Theng et al. (2025) introduced a human-guided multi-objective Bayesian optimization (MOBO) framework integrated with Gaussian process (GP) regression to optimize the textural properties of HMMAs produced through extrusion. The MOBO model captured the non-linear relationships between key extrusion parameters, i.e., moisture content, barrel temperature, and screw speed, and textural attributes such as hardness, chewiness, springiness, and cutting force. Through iterative prediction and experimentation, the system generated candidate process conditions that converged toward the textural characteristics of cooked chicken breast. The optimized formulations achieved hardness and cutting force values within -5.23% to -7.10% and -14.67% to 7.33% of the target chicken breast texture, respectively, demonstrating the capability of Bayesian optimization to identify favorable trade-offs among multiple objectives. This study highlights the potential of combining GP-based surrogate modeling with adaptive Bayesian search strategies to achieve precise control of extrusion parameters while minimizing experimental burden, marking an important step toward autonomous, data-driven optimization of plant-based meat texture. However, the robustness of such optimization frameworks may be constrained by the availability of high-quality datasets and their limited validation under variable industrial processing conditions.

Other AI-assisted approaches further reinforce this potential. Fan et al. (2013) showed that a computer vision system (CVS) coupled with an ANN could predict the hardness and gumminess of extruded foods based on color attributes (a^* , b^* , and L^*). The ANN outperformed linear fitting models, achieving higher predictive accuracy for hardness (R^2 = 0.9671 vs. 0.9558) and gumminess (R^2 = 0.9856 vs. 0.9429), highlighting the strong correlation between external color and internal physical attributes. In addition, St. Pierre et al. (2024) evaluated the texture of eight plant-based and animal meats by tension, compression, and shear tests simultaneously combined with a constitutive neural network model. However, TPA analysis has the capability of determining one-dimensional behavior at once. The model included deformation gradient (F) as an input, two hidden layers, and strain energy $\Psi(F)$ as an output. The network, by minimizing the loss function (error), selected the best model and parameters (R^2 = 0.91), highlighting the potential of the ANN model for real-time quality control in extrusion-based food manufacturing. Together, these studies demonstrate how AI models, ranging from regression and ensemble methods to ANNs, can not only predict textural properties of PBMA with high accuracy but also reduce reliance on traditional, labor-intensive testing methods. A recent advancement in this field is the development of ChewNet, a multimodal dataset containing in vivo (human participants) and in vitro (biomimetic chewing robot) mastication data of beef and plant-based burger patties (Fig. 7E-H). The dataset integrates high-resolution bolus images, chewing force profiles, and TPA metrics across sequential chewing cycles, providing a synchronized record of structural and mechanical changes during oral processing. Such comprehensive data enable the training and validation of DL models capable of predicting bolus texture and breakdown patterns directly from visual and mechanical inputs. By capturing both human-like and robotic mastication behaviors, ChewNet offers a unique benchmark for evaluating plant-based formulations against real meat, identifying structural gaps, and

supporting the design of PBMA with improved texture and mouthfeel. Its integration into AI-driven frameworks has the potential to reduce reliance on repetitive experimental trials, enhance model generalizability, and accelerate the development of plant-based products that more closely replicate the oral experience of animal meat (Akarawita et al., 2025). Despite these advances, the broader applicability of such models remains limited by data scarcity, potential dataset bias, and the difficulty of generalizing predictions across diverse processing conditions and ingredient systems.

6. AI in sensory evaluation and consumer acceptance

6.1. Sensory evaluation

Sensory properties, including texture, taste, and appearance, are essential factors that influence consumers' decisions to choose plant-based alternatives over animal-based foods. These characteristics play a crucial role in determining whether consumers prefer plant-based options (Giacalone et al., 2022). Sensory attributes are the main obstacles and texture is the second barrier for consumer acceptance, therefore, advanced sensory evaluation is critical for developing plant-based products. The inherent differences between animal protein and plant protein in the structure and size of protein molecules, the composition of amino acids, the sequences of peptides, and the chemical characteristics create challenges in trying to replicate the complex sensory qualities present in animal meat products (Caputo et al., 2023; Sha & Xiong, 2020). To overcome these challenges, novel technologies such as HME, shear structuring, 3D printing, electrospinning, and freeze structuring have been applied to create fibrous networks that resemble real meat (De Angelis et al., 2024; Ozturk & Hamaker, 2023). Despite these advances, studies indicate that animal-based meat is still preferred to plant-based and hybrid products, often due to unfamiliarity or differences in sensory quality (Caputo et al., 2023; Van Loo et al., 2020). Here, AI offers unique opportunities for sensory science by analyzing complex datasets to predict taste, texture, and overall acceptability. It can also integrate electronic sensors, robotics, and computer vision to evaluate appearance, packaging interactions, and consumer responses (Nunes et al., 2023). Different AI models, such as ANNs and computer vision systems, have been used to evaluate sensory attributes and predict product shelf-life (Addanki et al., 2022). Emerging tools, including brainwave analysis, have also been applied to capture consumer preferences with greater accuracy, reducing errors in interpreting sensory perceptions and supporting large-scale studies (Warnakulasooriya et al., 2020). Similarly, predictive modeling strategies can identify sensory drivers linked to consumer acceptance, enabling the design of products with higher market appeal (Marín-Obispo et al., 2021). For example, Sun et al. (2018) applied a support vector machine (SVM) regression model to predict pork color using computer imaging. Compared with subjective evaluation and colorimetric devices, SVM achieved higher accuracy and avoided errors caused by marbling and lean tissue variation. In another study, Sun et al. (2012) used SVM and multispectral imaging to predict beef tenderness, achieving 91% accuracy. These studies highlight the potential of AI-based models, such as SVM, as powerful tools for objective, non-destructive evaluation of sensory attributes, which can be readily adapted to improve the quality assessment of PBMA.

In recent years, a vast amount of research has been published on consumer perceptions of plant-based proteins, yet manually sorting and analyzing this information is time-consuming (Aschemann-Witzel & Peschel, 2019; Runte et al., 2024). To address this, Chen et al. (2021) applied text mining and Natural Language Processing (NLP) to extract sensory data and identify consumer trends. By processing academic papers through NLP-based preprocessing (e.g., tokenization, lemmatization, and stemming) and visualizing results with word clouds, the study revealed that pea protein has become the most widely studied plant-based source, while soy and wheat gluten also remain central in

product development. Frequently occurring terms such as acceptance, like, and dislike clustered alongside plant-protein keywords, indicating generally high consumer willingness toward PBMA compared with earlier alternatives. However, the authors noted that coding accuracy could be improved, as the system struggled to distinguish nuanced emotional expressions (e.g., “like” vs. “not like”). While text mining provides valuable insights into consumer sentiment, another emerging line of research seeks to connect physical properties of food with sensory perception more directly. In an innovative study, Kraessig et al. (2025) introduced a sensory-biased autoencoder, a specialized neural network designed to uncover non-linear relationships between rheological parameters (e.g., shear-thinning consistency k and flow index n) and perceived texture. Unlike conventional autoencoders, this model incorporated sensory panel scores (s) as a bias term in the decoder, ensuring that the reconstructed rheological parameters (k' and n') were explicitly aligned with human perception (Fig. 8). This unique design enabled the network to detect non-injective mappings, situations where different rheological profiles, such as varying combinations of consistency and shear-thinning behavior, produced the same perceived thickness. Remarkably, even when trained on a relatively small dataset, the model reconstructed rheological parameters with high accuracy and successfully predicted perceived texture outcomes. This approach offers practical benefits for PBMA design: (I) reducing reliance on large-scale sensory panels by predicting texture from rheology, (II) identifying multiple processing routes to achieve equivalent sensory outcomes, and (III) accelerating product development by linking engineering-level measurements to consumer experience. Together with text mining for consumer sentiment, such representation-learning frameworks highlight how AI can bridge the gap between physical formulation and sensory acceptance in PBMA.

Another promising approach for AI-assisted sensory evaluation is the use of fuzzy set theory combined with neural networks to model sensory quality and determine process control set points. In an early study by Kupongsak and Tan (2006), fuzzy sets are used to quantify the inherently “fuzzy” nature of human sensory responses, while neural networks are applied to model the nonlinear relationships between sensory attributes and processing variables. Multi-judge sensory responses are first expressed as fuzzy membership vectors, which capture the degree to which a product belongs to different sensory categories. For a single attribute evaluated across n fuzzy sets, the membership vector is defined as (Eq. 8):

$$\mu_i(x) = [\mu_1(x) + \mu_2(x) + \dots + \mu_n(x)] \quad (8)$$

where $\mu_i(x)$ represents the average membership grade of sample x in fuzzy set i (Eq. 9):

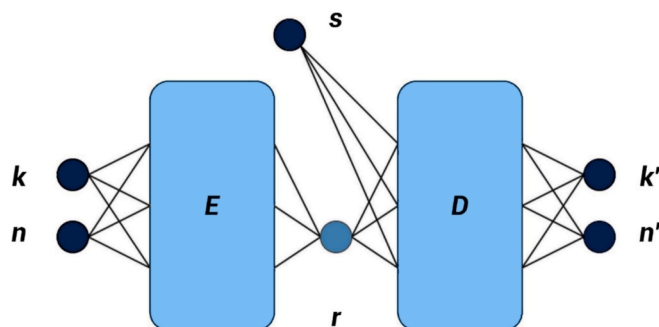


Fig. 8. Sketch of the autoencoder architecture with sensory bias. The encoder (E) compresses the rheological attributes (k, n) into a latent representation (r), while the decoder (D) reconstructs the attributes with the sensory score (s) as a bias, aligning physical properties with perceived texture; adapted from Kraessig et al. (2025).

$$\mu_i(x) = \frac{1}{m} \sum_{j=1}^m \mu_{ij}(x), i = 1, 2, \dots, n \quad (9)$$

Here, $\mu_{ij}(x)$ is the membership grade assigned by judge j , and m is the total number of judges. For multiple sensory attributes, the responses are arranged into a fuzzy membership matrix (Eq. 10):

$$Y = \begin{bmatrix} \mu_{1,1}(x) & \mu_{1,2}(x) & \cdots & \mu_{1,q}(x) \\ \mu_{2,1}(x) & \mu_{2,2}(x) & \cdots & \mu_{2,q}(x) \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{p,1}(x) & \mu_{p,2}(x) & \cdots & \mu_{p,q}(x) \end{bmatrix} \quad (10)$$

where p is the number of attributes and q the number of fuzzy sets for each attribute.

Neural networks are then trained to map these fuzzy matrices to processing variables, enabling both forward mapping (predicting sensory responses from process settings) and backward mapping (identifying process set points to achieve a target sensory profile). Validation using rice cake production showed that new products manufactured under neural network-predicted set points matched desired sensory target values with less than 9% error, demonstrating strong predictive performance (Kupongsak & Tan, 2006). This study underscores the potential of fuzzy logic–neural network hybrids in sensory-driven food design. For PBMA, such models could be applied to align processing conditions (e.g., extrusion temperature, shear, and hydration) with consumer-driven sensory targets (e.g., texture, chewiness, and juiciness), offering a systematic route to optimize both product quality and consumer acceptance.

6.2. Marketing

One of the major hurdles in marketing innovative PBMA is consumer willingness to pay. Despite increasing awareness of the environmental, sustainability, and health benefits of PBMA, many consumers remain reluctant to switch from conventional meat (Flint et al., 2023). Price is a particularly influential factor. While raw plant materials are generally inexpensive, post-processing, packaging, and distribution significantly increase production costs, resulting in higher retail prices compared with animal-based products (Manners et al., 2020). This price gap limits adoption, although projections suggest that plant-based proteins could become five to ten times cheaper than animal proteins by 2030–2035 due to rapid technological advancements (Tubb & Seba, 2019). AI can help overcome these barriers by analyzing production efficiency and optimizing processes to reduce costs. For example, AI-powered tools can evaluate energy consumption, waste generation, and processing speeds, allowing manufacturers to streamline production and improve sustainability (Cooper et al., 2024). Similarly, Decardi-Nelson & You (2024) demonstrated that integrating AI into advanced plant factories with artificial lighting (PFAL) systems reduced energy use by 25% while improving resource optimization for photosynthesis, transpiration, and respiration. Such improvements make plant-based production both more sustainable and cost-effective.

Another barrier is food neophobia, the reluctance to try unfamiliar foods. Neophobia is particularly pronounced among consumers who avoid alternative proteins, often due to skepticism toward new technologies or negative associations with earlier plant-based products, such as tofu products (Onwezen et al., 2021; Szenderák et al., 2022). While neophobia levels vary across demographics and regions, familiarity with ingredients in newer products has been shown to increase willingness to try PBMA. Addressing this barrier requires effective communication, positive tasting experiences, and product designs that highlight familiar flavors and ingredients (Siddiqui et al., 2022). Moreover, AI tools can be used for sentiment analysis of consumer opinions, enabling companies to detect and address neophobia-related concerns (D'Souza et al., 2024).

AI is also revolutionizing consumer insight generation and personalization. Traditional sensory panels and surveys are costly and limited in scale, but AI enables large-scale, data-driven analysis of consumer preferences. For example, Khilji et al. (2021) developed an ML-based recipe recommendation engine that personalizes plant-based meal suggestions based on user queries, lowering the barrier for consumers to explore alternative proteins. Similarly, Álvarez-Pato et al. (2020) employed multimodal AI systems, including facial emotion recognition (FER), galvanic skin response (GSR), and heart rate monitoring, to capture consumers' subconscious reactions to food samples. While FER alone had limited predictive power, its combination with physiological signals significantly improved accuracy, offering a powerful tool for understanding acceptance in real-world conditions. Beyond consumer testing, AI contributes to food production and distribution by predicting demand, minimizing overproduction, and reducing waste. It can also detect potential food losses and suggest alternative uses, thereby promoting more sustainable practices (Marcellin et al., 2024). Collectively, these applications illustrate AI's transformative role in overcoming marketing challenges for PBMA. By lowering production costs, analyzing consumer sentiment, enhancing personalization, and supporting sustainable supply chains, AI fosters greater consumer acceptance and strengthens the global market for plant-based meat products.

7. AI in nutritional profiling and health

Consumer adoption of PBMA largely relies on achieving sensory qualities similar to traditional meat; however, their long-term success and impact on public health depend critically on their nutritional and health profiles. PBMA presents a distinct “nutritional dichotomy,” offering significant advantages over conventional meat while also posing unique formulation challenges. PBMA are inherently free of dietary cholesterol, lower in saturated fat, and provide dietary fiber, a nutrient entirely absent in animal meat (Mariotti, 2025). This favorable profile translates to measurable health benefits; recent clinical trials and meta-analyses have shown that replacing conventional meat with PBMA can lead to significant reduced risks of type 2 diabetes and cardiovascular disease (Choręziak et al., 2025; Fernández-Rodríguez et al., 2024). However, PBMA often require fortification to match meat's micronutrient profile (e.g., vitamin B₁₂, iron, and zinc) and are frequently high in sodium. A primary hurdle is the lower bioavailability of minerals, as plant-based ingredients contain anti-nutrients like phytic acid that chelate iron and zinc, alongside incomplete essential amino acid profiles that necessitate careful protein blending (Hertzler et al., 2020; Toh et al., 2024). These formulation gaps underscore that not all plant-based products are automatically healthy, and attention is needed to reduce salt, enhance protein quality, and ensure adequate vitamins and minerals. Surveys of commercial PBMA products show that while they generally contain less saturated fat and more fiber than animal meats with lower protein quality, many have higher salt content, and only less than a quarter of products are fortified with key micronutrients like B₁₂ or iron (El Sadig & Wu, 2024). These limitations highlight the need for smart formulation strategies to deliver on the health promise of meat alternatives.

Beyond basic nutrition, PBMA can function as delivery vehicles for plant-derived bioactive compounds such as polyphenols, isoflavones, and phytosterols, that offer antioxidant and anti-inflammatory properties not found in animal products. This introduces a “nutritional paradox,” as many beneficial polyphenols are the same compounds classified as anti-nutrients (Alvarez-Leite, 2025; El Sadig & Wu, 2024). AI is crucial for navigating this complexity. For instance, an AI system can be tasked with creating a plant-based burger that matches the protein quantity of beef but with lower saturated fat and a specific fiber content; the algorithm will search vast combinations of plant proteins, oils, and binders to meet these nutritional goals alongside texture and flavor parameters. Such multi-objective optimization has already been demonstrated, Kuhl (2025) notes that AI can identify ingredient

combinations that maximize nutritional value while minimizing environmental impact, or enforce nutritional equivalence to an existing meat product. In practice, this might mean finding the optimal blend of, say, pea and rice protein to yield a complete amino acid profile, plus selecting a salt substitute or umami enhancer to reduce sodium chloride without sacrificing taste.

PBMAs offer a suitable opportunity to health-promoting bioactive compounds unique to plants. Cheminformatics and QSAR/deep-learning screens rapidly prioritize polyphenols and food-derived peptides with predicted antioxidant, anti-inflammatory, or metabolic activities, focusing scarce wet-lab resources on the highest-value candidates (Park et al., 2022; Staszak et al., 2022). For example, AI tools like PhyteByte use ML model to screen food compound databases (FoodDB or FoodAtlas) against pharmacological targets, identifying phytochemicals with specific predicted health benefits, such as modulating the metabolic regulator PPARG (Westerman et al., 2020; Youn et al., 2024). Similarly, toxicity prediction algorithms like DeepTox can screen plant-derived compounds for safety, ensuring that novel bioactive ingredients meet regulatory standards before formulation (Mayr et al., 2016). Likewise, ML has been applied to protein hydrolysate databases to discover new bioactive peptides. These are short sequences of amino acids released from plant proteins that can have drug-like effects (for example, acting as ACE inhibitors, or hormone modulators). Doherty et al. (2021) reported the AI-driven identification and preclinical validation of a novel pea-derived peptide that improves insulin sensitivity. Incorporating such AI-identified peptides into a plant-based meat formula could allow the product to actively improve metabolic health in consumers, a value proposition far beyond what traditional meat offers.

A final bottleneck in PBMA development is the slow and resource-intensive process of verifying nutrient bioavailability, which traditionally relies on complex in vitro digestion models or costly in vivo trials. AI-driven in silico solutions, such as Mechanistic Digestion Models, are emerging to accelerate this workflow by computationally simulating the entire human gastrointestinal tract (van Aken, 2024b). Notably, the model is designed to interface with organ-on-a-chip systems and human digital twin frameworks (van Aken, 2024a). By integrating predictive modeling with mechanistic food science, AI supports the rational design of next-generation PBMAs that not only replicate meat's sensory profile but also deliver enhanced bioactive content for preventive health benefits, accelerating the development timeline from candidate identification to market-ready formulations and reducing the reliance on extensive lab-based validation.

8. Limitations and future research directions

Although AI provides powerful tools for the formulation, processing, and consumer assessment of PBMAs, its current applications face several limitations that must be acknowledged. These limitations, summarized in Table 2, highlight the main challenges that hinder large-scale adoption of AI in PBMAs and point toward areas where future research is urgently required.

- **Data availability, quality, and transferability:** One of the most pressing challenges is the lack of large-scale, standardized, and openly accessible datasets. Many AI models for PBMAs are trained on limited, product-specific datasets, which hinders generalizability and reproducibility across different formulations, processing techniques, and consumer demographics. In addition to data scarcity, systematic biases in datasets, such as overrepresentation of specific protein sources (e.g., soy or pea), processing conditions, or regional consumer preferences, can lead to skewed model predictions and reduced applicability in diverse contexts. Furthermore, most available datasets fail to capture multimodal aspects of PBMAs, such as chemical composition, protein–polysaccharide interactions, rheological signatures, structural morphology, and sensory evaluations. Without integration of these heterogeneous data streams, AI models

Table 2
Current limitations of AI applications in PBMAs and proposed future research directions.

Limitations	Description	Future Research Directions
Data scarcity and fragmentation	Limited, product-specific datasets that lack multimodal information (e. g., chemical, rheological, structural, and sensory data).	Develop open-access, multimodal databases integrating composition, rheology, structural imaging, sensory, and consumer data for cross-validation of AI models.
Model interpretability ("black box" issue)	Deep learning and advanced ML models provide high accuracy but limited transparency, reducing trust among scientists, regulators, and consumers.	Integrate XAI, physics-informed ML, and interpretable models that link predictions to mechanistic understanding of food systems.
High computational cost and expertise requirement	Advanced AI methods (e.g., GANs, RL, hybrid models) demand significant computational power and specialized knowledge, limiting SME adoption.	Develop user-friendly AI platforms with simplified interfaces for food scientists; expand access to cloud-based AI tools and training.
Scalability and industrial validation	Most AI applications remain at lab- or pilot-scale; performance may not translate to large-scale production with raw material and equipment variability.	Validate AI models under industrial conditions; develop digital twins of PBMA production lines to simulate and optimize full-scale processes.
Regulatory and ethical concerns	Lack of clear regulatory frameworks for AI-assisted food design; questions about data ownership, privacy, and consumer safety.	Establish international standards for AI-driven food innovation; ensure compliance with food safety and labeling laws; address ethical issues in data use.
Consumer acceptance and cultural adaptation	AI models often neglect regional preferences, food neophobia, and socio-cultural drivers of consumption.	Incorporate consumer preference data, cultural dietary habits, and personalization into AI models to design products tailored to specific populations.
Sustainability integration	AI applications often focus on functionality rather than environmental impact.	Couple AI with LCA, carbon footprint modeling, and water-use prediction to guide sustainable PBMA innovation.

Abbreviations: AI, artificial intelligence; PBMAs, plant-based meat alternatives; ML, machine learning; GANs, generative adversarial networks; LCA, life cycle analysis; RL, reinforcement learning; SMEs, small- and medium-sized enterprises; XAI, explainable artificial intelligence.

risk overfitting and poor transferability. Transfer learning offers a promising strategy to address PBMA-specific data scarcity by adapting models pre-trained on larger datasets from related food systems, such as dairy, cereal, and conventional meat products, to plant-based applications. By leveraging previously learned representations, transfer learning can reduce data requirements, improve model robustness, and accelerate the development of predictive models for tasks such as texture prediction, process optimization, nutritional profiling, and consumer acceptance.

- **Model interpretability and transparency:** A major limitation of many AI approaches, particularly deep learning models, is their "black box" nature. While these models often achieve high predictive accuracy, their lack of interpretability limits scientific transparency and hinders trust among researchers, industry stakeholders, and regulatory bodies (Ng & Tan, 2025). In the context of food systems, explainability is particularly critical, as decisions related to formulation, safety, and labeling must be transparent and justifiable. Moreover, consumer acceptance of AI-assisted food design may

depend on the ability to clearly explain how ingredient choices and processing decisions are made. Explainable AI (XAI) techniques, such as feature importance analysis and model-agnostic interpretation methods (e.g., SHAP), can help identify key variables driving predictions and translate them into physically meaningful relationships. Therefore, integrating XAI, physics-informed machine learning, and interpretable modeling frameworks is essential to link predictions with underlying food structure and functionality, while supporting regulatory approval and consumer confidence.

- **Computational costs and expertise:** Advanced AI frameworks, including reinforcement learning, generative models, and hybrid mechanistic–statistical approaches, often require substantial computational resources, high-quality data infrastructure, and specialized expertise. These requirements can limit adoption, particularly among small and medium-sized enterprises (SMEs), which represent a large portion of the PBMA sector. In addition to hardware and software costs, successful implementation also requires interdisciplinary expertise spanning data science, food engineering, and process optimization. To enable broader adoption, future efforts should focus on developing user-friendly AI platforms, cloud-based solutions, and standardized workflows that can be integrated into existing food production systems with minimal technical barriers.
- **Scalability and validation:** Many AI-driven PBMA studies remain limited to laboratory-scale or pilot-scale experiments. The transition to industrial-scale production introduces new sources of variability, including raw material heterogeneity, equipment design, and supply chain constraints. In particular, batch-to-batch variability in plant protein raw materials, arising from differences in cultivar, growing conditions, harvest season, and processing history, can significantly affect composition and functional properties, thereby reducing model accuracy and generalizability. Scaling AI predictions across these complex environments remains a challenge. Moreover, while AI can optimize processing parameters such as extrusion temperature, shear, and moisture content, there is limited validation of these optimized models under real-world industrial conditions.
- **Regulatory and ethical considerations:** The integration of AI into food systems also raises regulatory and ethical questions (Yu et al., 2025). Current regulatory frameworks are not fully adapted to AI-assisted food design, particularly for systems involving generative models, predictive sensory evaluation, or automated decision-making. Future frameworks are likely to require model transparency, data traceability, validation and reproducibility of predictions, and compliance with food safety and labeling standards. In addition, issues related to data ownership, privacy, and algorithmic bias must be addressed. Federated learning and other privacy-preserving AI approaches offer promising solutions by enabling multiple organizations to collaboratively train predictive models without sharing raw proprietary formulation data, thereby preserving confidentiality while benefiting from larger and more diverse datasets. Ensuring compliance with food safety regulations and clean-label expectations is essential for building consumer trust. In this context, transparent and explainable AI systems will play a key role in facilitating regulatory approval and ensuring ethical and responsible use of data.

To overcome these limitations, several promising pathways can be prioritized. **First**, data integration remains fundamental. Building open-access, multimodal databases that capture chemical composition, structural morphology, rheological signatures, sensory evaluation, and consumer preference data would provide a robust foundation for AI modeling. Such comprehensive datasets would enable cross-validation and benchmarking of AI models, reducing overfitting and improving generalizability across diverse formulations and processing conditions. **Second**, the integration of AI with omics technologies such as genomics, proteomics, metabolomics, and lipidomics offers significant potential

for accelerating the discovery of novel proteins and mapping their functional roles in PBMA. For instance, proteomics can elucidate protein structure–function relationships, metabolomics can identify flavor-active and bioactive compounds, and lipidomics can guide fat structuring and mouthfeel optimization in plant-based systems. By linking molecular-level insights with predictive modeling, AI can help identify promising protein sources, predict their techno-functional behavior, and guide formulation strategies more efficiently. However, these approaches should be viewed as complementary to experimental and trial-and-error methods, which remain essential for validating predictions and capturing complex food system behaviors. **Third**, generative modeling and digital twin technologies represent powerful emerging tools. Generative AI can be used to design novel protein sequences and simulate ingredient interactions, while digital twin systems can replicate entire production pipelines, from raw material processing to final sensory evaluation, in a virtual environment. These tools would allow researchers and manufacturers to optimize formulations and processes before scaling to physical trials, saving both time and resources. **Fourth**, sustainability should be an integral component of AI applications in PBMA. Several AI-driven tools for life cycle assessment (LCA), carbon footprint prediction, and resource-use optimization have already been developed in adjacent domains, including agriculture, food manufacturing, and packaging, and these approaches can be readily adapted to PBMA production systems (Arya et al., 2024; Chinnappan et al., 2025). Expanding predictive frameworks to incorporate LCA, carbon footprint assessment, and water-use analysis will ensure that plant-based alternatives not only replicate the sensory and functional properties of meat but also meet global sustainability targets. Such tools could help companies balance product innovation with environmental responsibility. **Fifth**, personalization and cultural adaptation are increasingly important in expanding PBMA acceptance. AI-driven frameworks that integrate consumer preference data, regional dietary habits, and nutritional needs can support the design of products tailored to specific markets. This consumer-centered approach would address barriers such as food neophobia and cultural resistance while also enabling the development of personalized nutrition solutions. **Finally**, integration of all the different areas, from marketing to ingredient sourcing, formulation, processing, and consumer liking under one framework is paramount, as currently many of those solutions are isolated and incompatible. To do that, interdisciplinary collaboration is essential. The successful application of AI in PBMA requires strong partnerships between food technologists, data scientists, rheologists, sensory scientists, behavioral researchers, and regulatory experts. Such collaborations will ensure that AI models are not only technically robust but also consumer-centered, ethically sound, and aligned with regulatory frameworks.

9. Conclusion

AI technologies, ranging from supervised and unsupervised learning to RL, hybrid mechanistic–statistical models, and DL, have demonstrated clear advantages in multiple stages of PBMA innovation. In formulation, AI can predict protein–polysaccharide interactions, guide optimal ingredient blending, and apply polymer blending laws to simulate rheological behavior. In processing, AI enables efficient optimization of extrusion and 3D printing parameters, reducing trial-and-error experimentation while enhancing fibrous structure formation. In quality evaluation, AI models can accurately predict textural and sensory outcomes from compositional and rheological data, offering alternatives to costly and labor-intensive sensory panels. Integrating AI-driven nutritional profiling and bioavailability modeling offers a promising avenue for designing targeted functional foods with greater health benefits. Furthermore, AI's integration into consumer science, through sentiment analysis, market prediction, and personalization, provides valuable insights into overcoming barriers such as food neophobia and price sensitivity.

Despite these advances, several critical challenges must be addressed to enable reliable and large-scale implementation. Future research should prioritize (i) the development of standardized, open-access, and multimodal datasets to improve model robustness and reduce bias; (ii) the integration of explainable and physics-informed AI models to enhance interpretability and regulatory acceptance; (iii) systematic validation of AI models under industrial processing conditions to ensure scalability; and (iv) the incorporation of sustainability metrics, such as life cycle assessment and resource-use modeling, into AI-driven design frameworks. In parallel, closer collaboration between food scientists, data scientists, and industry stakeholders will be essential to translate AI innovations into practical applications.

Overall, rather than representing a purely transformative solution, AI should be viewed as an enabling framework that can support more efficient, data-driven PBMA development when combined with domain knowledge and experimental validation. By addressing current limitations and focusing on actionable research directions, AI has the capacity to accelerate the transition of PBMA from emerging alternatives to widely adopted, sustainable food solutions.

CRedit authorship contribution statement

Roya Aghagholizadeh: Writing – original draft, Methodology, Conceptualization. **Mohammad Tarahi:** Writing – original draft, Visualization, Project administration, Methodology. **Pranav Gupta:** Writing – original draft, Methodology. **Manisha Singh:** Writing – original draft, Methodology. **Ilias Tagkopoulos:** Writing – review & editing, Conceptualization. **Mina Dokouhaki:** Writing – review & editing, Supervision, Project administration, Conceptualization.

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Declaration of competing interest

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

Data availability

The article includes any data that support the findings of this study. No new data were created or analyzed in this study.

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