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Review

Cultured Meat in the Age of Artificial Intelligence: Is the Time Now?

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Abstract

The unsustainable trajectory of global meat consumption continues to create an urgent need for alternatives or to rethink livestock systems. While plant-based options are available, consumer acceptance remains limited due to sensory shortcomings and neophobia. In contrast, cultured meat has the potential for theoretical biological equivalence to conventional meat; however, the development of cultured meat is currently constrained by unresolved biological and technical challenges. Meanwhile, artificial intelligence (AI) has emerged as a transformative tool for addressing these limitations. This systematic review evaluates the potential for AI to optimize the efficiency of cultured meat production, enhance sustainability, and accelerate market introduction. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines and included 28 studies. Key findings are presented across several critical domains. Computational modeling can compensate for data scarcity by simulating industrial scenarios where experimental data are limited. AI algorithms are also shifting media development from trial-and-error approaches to predictive optimization, enabling the identification of cost-effective plant-based alternatives to animal serum. In tissue engineering, strategies vary between optimizing biological efficiency and digitally reconstructing the architecture of conventional meat. These production advances are supported by quality control systems that combine non-invasive visual monitoring with predictive safety analysis for real-time hazard detection. AI also extends to consumer intelligence, moving from passive sentiment analysis to active engagement that addresses misinformation and presents cultured meat as a transparent, personalized nutrition option. Overall, this review establishes a foundational framework that synthesizes fragmented research. Additionally, this review reveals critical economic constraints that may have previously been obscured by technical optimism. Moreover, this review identifies strategic priorities that emphasize systemic integration, open data ecosystems, and consumer-aligned value propositions, all of which are essential to translating laboratory achievements into commercial reality.

Keywords: cellular agriculture; artificial intelligence; deep learning; cell-based food; consumer intelligence; machine learning

1. Introduction

The global population is projected to reach approximately 9.7 billion by 2050, with meat consumption demand expected to rise substantially over the coming decades [1]. However, this trajectory could be unsustainable regarding the environmental impact, as current livestock production accounts for approximately 12% of global greenhouse gas emissions, while also driving land degradation, water scarcity, and biodiversity loss [2]. Beyond environmental impact, sustainability encompasses food safety and healthiness, economic viability, and cultural acceptability [2]. Thus, this scenario requires revisiting livestock systems [3] or identifying alternatives that reduce environmental impact while meeting requirements of food safety, nutritional equivalence, economic feasibility, and consumer acceptance.

A growing body of literature argues that the environmental impact of livestock production is often overstated or misinterpreted [3]. Revisiting conventional livestock systems represents a valuable and more immediate pathway to reduce the environmental impact of meat production [3]. In parallel, recent literature explores alternative protein sources as a complementary strategy. Within this landscape, cultured meat has attracted significant scientific and industrial attention as one of the alternatives under active investigation.

In recent years, interest in sustainable nutrition has increased research on alternative protein sources, which present different trade-offs between production efficiency, scalability, and nutritional quality [4]. Options such as insects and microalgae have demonstrated favorable environmental impact and nutritional profiles rich in high-quality protein and bioactive compounds. However, their direct consumption often faces cultural resistance and processing challenges [5]. Similarly, fermentation-derived proteins, including mycoprotein and bacterial protein, offer scalable solutions exemplified by commercial products like Quorn and Solein. Nevertheless, their production costs remain substantially higher than those of established agricultural crops [6]. Conversely, conventional plant proteins such as soy and pea remain the industrial standard due to their economic viability. To satisfy consumer sensory expectations, these ingredients are predominantly formulated into plant-based meat analogues. While this market has experienced significant growth and sensory improvements, population reach remains constrained by persistent neophobia and the inability to replicate the sensory complexity of animal tissue [7].

Furthermore, meat consumption represents a deeply rooted cultural tradition across many societies. Demographic projections indicate that despite the rise of plant-based alternatives, sustainability challenges persist. Consumers often perceive these products as inferior substitutes requiring dietary adaptation. In this context, cultured meat emerges as a potential alternative. Unlike plant-based analogues, which face intrinsic limitations in mimicking conventional meat characteristics [8,9], cultured meat offers the potential for complete biological and sensory equivalence [10]. Indeed, meat attachment reduces the acceptance of plant-based substitutes but does not affect cultured meat acceptance, which consumers perceive as authentic meat produced through an alternative method [11,12]. Consequently, cultured meat represents a potentially valuable alternative for consumers who reject plant-based options, offering a viable pathway to mitigate environmental impact amid rapid population growth.

However, while cultured meat holds high potential for consumer adoption, it currently lags behind plant-based analogues in technological maturity and environmental efficiency. Moreover, it faces complex regulatory landscapes; for instance, under European Union legislation, cultured meat is not classified as meat [13] (a designation reserved for slaughter-derived products), but is governed by the Novel Food framework [14]. Furthermore, the term cultured meat is not formally recognized by the FAO, which classifies it under the broader category of cell-based food, defined as foods, ingredients, or additives produced using cells isolated from animals, plants, or microorganisms [15]. Beyond regulatory barriers, as an emerging technology, the sector faces substantial hurdles regarding scalability and energy consumption. Consequently, although conceptually more sustainable than conventional livestock, current cultured meat production systems face environmental challenges. Their production costs also remain significantly higher than those of plant-based counterparts, driven by low process efficiencies and high operational expenses [16,17].

To overcome these technoeconomic barriers, Artificial Intelligence (AI) has emerged as a transformative catalyst. As noted by Wang et al. [18], AI has revolutionized scientific discovery by enabling researchers to process vast amounts of unlabeled data, exploit underlying structures to improve model accuracy, and generate novel designs from diverse modalities. Implementing this technology in the food industry is essential, both to reduce the sector's contribution to global warming and to address the scalability crisis of cellular agriculture. In this context, the integration of AI into cultured meat production holds considerable promise for shifting the paradigm from empirical trial-and-error to predictive optimization. This approach allows for the systematic evaluation of culture substrates, bioprocess parameters, and operational conditions. Nevertheless, technical optimism should not obscure economic realities. The gap between AI potential and the practical constraints of commercial-scale production warrants critical examination.

Therefore, the objective of this systematic review is to evaluate the potential of AI implementation in cultured meat development to optimize production efficiency, enhance sustainability, and accelerate global market introduction, thereby establishing a foundational framework to guide future research and industrial scaling.

2. Literature Search

This systematic review was conducted in accordance with the PRISMA guidelines [19]. The literature search was performed across PubMed, Scopus, and Web of Science databases in October 2025 and subsequently updated in December 2025 to capture the latest publications. The search strategy employed the following keywords: (“In Vitro Meat*” OR “Cell-Based Meat*” OR “Cell Based Meat*” OR “Cultivated Meat*” OR “Cultured Meat*” OR “Lab-Grown Meat*” OR “Lab Grown Meat*” OR “Laboratory-Grown Meat*” OR “Laboratory Grown Meat*”) AND (“Artificial Intelligence” OR “AI” OR “machine learning” OR “deep learning” OR “Computational Intelligence” OR “Neural Networks” OR “Pattern Recognition” OR “Robotic*” OR “Automation” OR “Industry 4.0”), searching by title, abstract, and keywords. No year or language restrictions were applied, as the substantial majority of retrieved records were published after 2020, reflecting the emerging nature of this research domain.

The search yielded 193 records (61 from Scopus, 43 from PubMed, and 89 from Web of Science). After removing duplicates, 115 unique records were screened by title and abstract, and, when necessary, by full-text examination. Inclusion criteria comprised original research articles and reviews, evaluating the application of AI, machine learning, or related computational methodologies in cultured meat production, including bioprocess optimization, media formulation, tissue engineering, quality control, and consumer intelligence. Studies were excluded if they mentioned AI or computational methods solely in a tangential or speculative manner without demonstrating direct application or methodological implementation in cultured meat contexts. Additionally, articles focusing exclusively on conventional meat processing or plant-based meat analogues without addressing cellular agriculture were excluded. After title and abstract screening, full-text assessment was performed, resulting in 28 studies included in this systematic review. A flow diagram detailing the study selection process is shown in Fig. 1.

3. Results and Discussion

The systematic search reveals that AI integration is not limited to isolated technical challenges but spans the entire cultured meat production process. Key findings have been outlined across several critical domains (Fig. 2), encompassing upstream processes such as media formulation and cell line development, core production challenges involving bioprocess design and tissue engineering, and down-

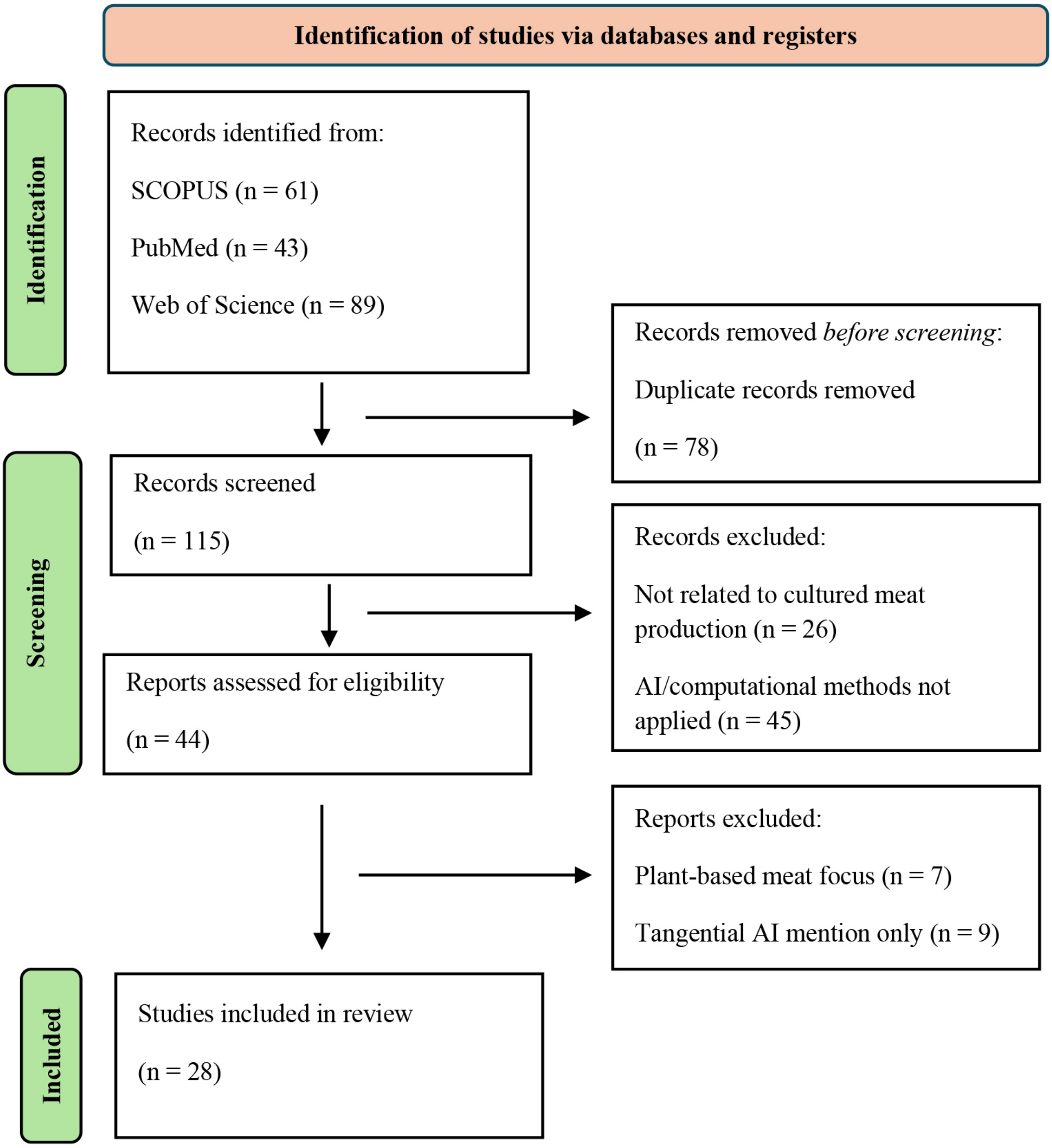

Fig. 1. Literature search flowchart with database and record searches.

stream quality assurance. This integrated framework illustrates how machine learning algorithms establish feedback loops between these distinct phases, shifting from empirical trial-and-error to predictive optimization across the production pipeline.

3.1 Data Scarcity and Quality Constraints

The transition of cultured meat from laboratory-scale prototypes to industrial viability is currently hindered by high production costs, variability in bioprocesses, and the complexity of replicating native tissue architecture. Commercial-scale production requires significant technological advances; however, the sector faces a foundational data limitation [20]. The industry lacks robust operational data from pilot-scale and commercial-scale facilities, precluding the validation of scalability assumptions or the prediction of real-world manufacturing performance. This data gap extends to all critical dimensions. Recent life cycle assessments reveal that existing sustainability claims predominantly rely on theoretical laboratory-scale data rather than commercial-scale metrics. As Hu [21] and Smetana et al. [6] note, this lack of practical data makes it difficult to es-

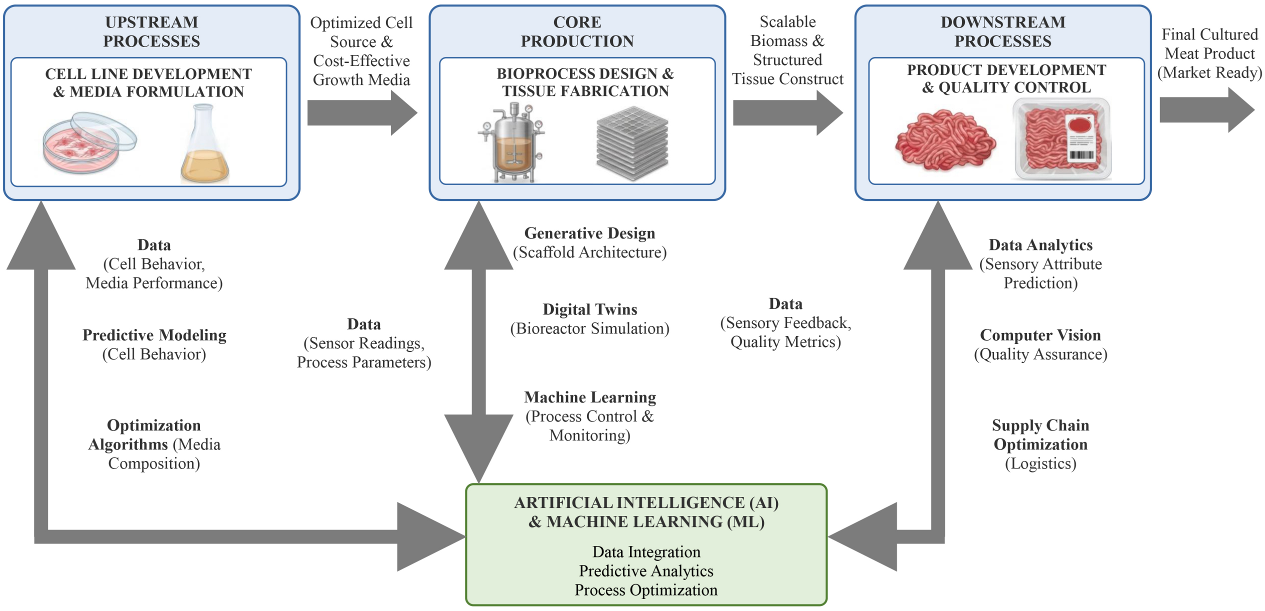

Fig. 2. Integrated application of AI across the entire cultured meat production.

timate the real environmental impact of industrial production.

Recent literature suggests that the convergence of AI and machine learning with cellular agriculture, often framed as Industry 4.0, is becoming a key enabler for bridging this gap. Several studies support a shift beyond trial-and-error experimentation toward predictive bioprocess modeling. Ng and Tan [22] and Todhunter et al. [23] highlight that machine learning algorithms are essential for exploring the multi-parametric design space, ranging from seed cell identification to contamination detection. However, Grzelak et al. [24] argue that the gap between the theoretical potential of these algorithms and the limited data availability renders many predictive models ineffective. To resolve this, they propose implementing smart automation platforms integrating robotics and sensing technology to streamline experimental data collection.

Beyond biological data, the lack of standardized operational datasets limits the implementation of AI-integrated processing technologies. Suychinov et al. [20] highlight the importance of integrating AI with industrial Internet of Things sensors (networked devices that continuously collect and transmit real-time operational data). This integration supports biological process monitoring, predictive maintenance, and energy optimization, which are key aspects to reducing the high operational costs of cultured meat production. According to their analysis, AI algorithms can process historical performance data to predict equipment failures and optimize energy-intensive systems such as heating, ventilation, air conditioning and refrigeration in real-time. Without high-quality training data from commercial-scale processing lines, these potential gains, which include automated defect detection via computer vision and hyperspectral imaging, remain theoretical.

Furthermore, the data bottleneck extends beyond technical constraints to encompass sociotechnical dimensions. Chiles et al. [25] argue that the proprietary nature of current cellular agriculture datasets creates knowledge silos that limit the training of generalized models. They advocate for shared data ownership and shifting towards open science frameworks. From a computational perspective, Ng and Tan [22] suggest using strategies such as transfer learning and federated learning to apply pre-trained models from related biomedical fields without compromising proprietary data. Once data pipelines are established, these models can feed into smart bioprinting factories [26], where AI drives process optimization through real-time feedback loops. This approach could generate the synthetic data needed to validate industrial life cycle assessments, which currently lack scale-up data [6,21].

Computational approaches that embed mechanistic knowledge into AI architectures, such as Physics-Informed Neural Networks [27,28] and Computational Fluid Dynamics frameworks [29], offer complementary pathways for predicting industrial-scale performance from limited experimental datasets. However, validation at pilot facilities remains essential for commercial translation [22]. These computational strategies, combined with the data infrastructure solutions described above, establish the foundation for addressing specific production challenges.

3.2 Cell Culture Media Optimization

Building upon these data infrastructure foundations, the following sections address specific production challenges, beginning with media formulation. The optimization of cell culture media remains the most resource-intensive aspect of cellular agriculture and a primary barrier to both commercial feasibility and environmental sustainability. Risner et al. [30] and Sinke et al. [31] identify energy consumption and the reliance on animal-derived components as critical hotspots. Without optimization, the global warming potential of cultured meat could exceed that of conventional beef in certain scenarios. These findings show that achieving economic and environmental viability requires media formulations that replace fetal bovine serum, the primary animal-derived ingredient, and reduce energy demands. These objectives are beyond the scope of traditional univariate experimentation.

To address this multifactorial challenge, AI-driven methodologies allow the systematic exploration of high-dimensional design spaces previously inaccessible through traditional experimentation. The literature presents two complementary AI-driven approaches that extend beyond classical experimentation: *de novo* optimization, which algorithmically generates novel formulations, versus intelligent screening of existing candidates. Within *de novo* approaches, two different strategies can be identified: extrinsic optimization of media formulations, and intrinsic reprogramming of cellular metabolism through AI-guided synthetic biology.

Representing the extrinsic optimization approach, Nikkhah et al. [32] demonstrate the efficacy of *de novo* optimization using a hybrid AI framework on zebrafish (*Danio rerio*) cell lines. By integrating response surface methodology with radial basis function neural networks and multi-objective genetic algorithms, they successfully modeled non-linear interactions to simultaneously minimize environmental impact and production costs while maximizing cell growth. This approach directly addresses the energy and cost constraints identified by Risner et al. [30], achieving formulations that reduced global warming potential by 60–65% and costs by 20–24%.

Complementing this extrinsic optimization, Yin et al. [33] propose an intrinsic *de novo* paradigm via AI-integrated synthetic biology. Rather than merely adjusting external ingredient concentrations, this approach utilizes top-down and bottom-up engineering to reprogram the cellular machinery itself. Yin et al. [33] detail the construction of microbial cell factories (e.g., engineered Pichia pastoris or Bacillus subtilis) for industrial-scale production. These systems can synthesize high-cost growth factors such as FGF2 and insulin, as well as serum proteins such as albumin. Furthermore, they propose the design of autonomous genetic circuits, utilizing CRISPR-Cas9 systems, that allow cells to self-regulate their transition from proliferation to differentiation based on environmental cues (e.g., sensing lactate levels or specific inducer molecules). This smart cell strategy could theoretically eliminate the need for complex, multi-stage media exchanges, thereby reducing bioprocess complexity. However, Yin et al. [33] also caution that these genetically modified lines face stricter regulatory scrutiny compared to non-GMO optimization strategies such as those proposed by Nikkhah et al. [32].

In contrast to *de novo* generation, an alternative AI-driven strategy involves the intelligent screening of existing candidates. Isaac et al. [34] provide a comprehensive framework for this approach, focusing on machine learning classifiers that evaluate the bioactivity of peptides derived from plant protein hydrolysates. These hydrolysates are cost-effective alternatives to fetal bovine serum for cultured meat media. Hydrolysates contain thousands of peptides per product, making experimental validation prohibitively resource-intensive. Isaac et al. [34] systematically characterize machine learning tools designed to predict key bioactivities relevant to cell culture growth: antioxidant, anti-inflammatory, antimicrobial, and growth factor activities. Their analysis reveals that while approximately 50 classifiers exist for antimicrobial prediction and 16 for anti-inflammatory activity, only five tools predict antioxidant activity and just two address growth factor or cell signaling functions. These last two categories are critical for media optimization. These classifiers employ algorithms ranging from random forests to convolutional neural networks, trained on specific peptide databases, to identify bioactive sequences based on physicochemical properties, sequence patterns, and structural features. The screening approach offers distinct advantages: it relies on existing knowledge encoded in bioactive peptide databases, poses lower regulatory hurdles than genetically modified approaches, and allows rapid *in silico* filtering of hydrolysate compositions to match specific cell line requirements.

However, significant methodological limitations constrain screening-based approaches. Isaac et al. [34] conducted independent validation and found substantial performance gaps. Models achieved area under the curve scores barely above 0.5 (random classification), with poor sensitivity causing bioactive peptides to be systematically overlooked during screening. These failures result from three critical gaps: (1) insufficient training dataset sizes, with most classifiers trained on fewer than 2000 peptides; (2) unreliable negative datasets, as non-bioactive peptides are rarely experimentally validated and are instead computationally inferred, introducing label noise; and (3) limited generalizability, with models performing well only on specific sequence types. Isaac et al. [34] emphasize that molecular databases require significant improvement before machine learning-based screening can effectively replace wet-lab validation. Until these foundational data quality issues are resolved, AI-driven screening remains a complementary tool rather than an independent method. This highlights the continued need for hybrid approaches that integrate computational prediction with targeted experimental confirmation.

3.3 Tissue Architecture Replication

Beyond media costs, replicating the native tissue architecture represents a critical challenge. While media optimization addresses cost, the replication of texture and mouthfeel remains the primary determinant of consumer acceptance. Studies such as Broucke et al. [35] report the challenge of replicating the complex muscle architecture, fibrillar organization, fat marbling patterns, and amino acid profile of conventional meat. This gap creates a sensory disconnect, leading to perceptions of unnaturalness. Furthermore, consumer rejection based on disgust responses or reactions resembling the uncanny valley effect remains a dominant psychological barrier [5,36]. Thus, the challenge is not merely structural but biomimetic: ensuring the engineered construct is indistinguishable from native tissue.

However, replicating meat structure does not guarantee biological equivalence. As highlighted by Fraeye et al. [37] and Olenic and Thorrez [38], current cultured tissues predominantly consist of immature, embryonic-like fibers that lack the biochemical complexity of adult muscle. Crucially, the conversion of muscle into meat relies on specific post-mortem metabolic processes, such as pH decline, rigor mortis, and enzymatic proteolysis, which are fundamental for developing characteristic texture and flavor. Yet, as Purslow [39] emphasizes, protocols to replicate these essential post-mortem transformations in bioreactor-harvested cells are currently non-existent. Beyond post-mortem processes, nutrient digestibility represents an additional critical aspect. Even when compositional similarity is achieved, nutritional value may differ substantially due to differences in digestibility and nutrient absorption. In this sense, cultured meat would need to replicate these nutritional properties before claims of biological equivalence could be validated [37]. Until these biological mechanisms are reproduced and supported by transparent data, claims of nutritional and sensorial equivalence remain speculative [40].

While post-mortem aging, digestibility, and bioavailability remain critical downstream hurdles, the sector's immediate priority is scalable tissue replication. AI is currently applied to address the structural constraints of this phase. Heine et al. [41] argue that biofabrication technologies originally developed for biomedical applications must be adapted to introduce automation and standardization, thereby accelerating the path to market. Li et al. [42] propose an AI-driven scaffold design approach that integrates material selection with bioreactor parameters to address this. Their approach focuses on engineering scaffold-cell interactions to promote myogenic differentiation. By controlling pore size and fiber orientation, scaffolds can regulate cell fate through mechanotransduction pathways.

In contrast to this computational generative approach, Wu et al. [43] propose a reverse engineering strategy based on biomimicry. Since current generative models tend to oversimplify real tissue complexity, they utilized micro-computed tomography (µCT) to capture the high-resolution architecture of porcine muscle. Their methodology involved a hybrid fabrication process: first, a computational segmentation algorithm extracted precise 3D models of muscle and fat domains from the µCT data. Subsequently, these digital models guided an embedded bioprinting system to deposit adipocytes within a cast hydrogel matrix with micron-level positional accuracy. This approach contrasts sharply with Li et al. [42], who prioritize the optimization of mechanical properties (stiffness, porosity) over morphological accuracy. While generative models allow for the creation of idealized scaffolds that maximize cell differentiation efficiency [42], data-driven replication aims to satisfy the consumer visual and textural expectations by physically recreating the irregular marbling patterns found in nature [43]. These complementary approaches (functional optimization and sensory authenticity) suggest that hybrid strategies integrating both may offer the most promising pathway forward.

Both strategies, however, face the challenge of objectively demonstrating scaffold performance beyond qualitative assessments, necessitating robust quantitative validation methods. In this context, Lanaro et al. [44] demonstrated the use of computer vision to quantify cell bridging kinetics, providing objective metrics to ensure scaffolds meet the rigorous sensory standards [35]. The development and optimization of this standardized computational screening methods remain critical priorities, as these tools enable systematic pre-selection of scaffold candidates before resource-intensive consumer sensory testing. Establishing such standardized validation frameworks will be essential for accelerating the translation of engineered constructs from laboratory prototypes to market-ready products.

The computational generative and biomimetic approaches described above require sophisticated fabrication infrastructure. To avoid this complexity, Ong et al. [45] used AI-driven screening to identify plant materials with naturally occurring structural mimicry. Using a deep convolutional neural network trained to recognize marbling patterns, they identified jackfruit (*Artocarpus heterophyllus*) as a valuable candidate. Its natural vascular architectures resemble meat marbling, and its polyphenol content allows color control to mimic raw chicken, pork, or beef. This biomimetic screening approach has several advantages. It eliminates the need for sophisticated bioprinting infrastructure and provides food-grade scaffolds that address consumer naturalness concerns. In addition, it demonstrated approximately an 8% improvement in consumer perception of cell-based meat products. However, critical limitations constrain this strategy. The approach is inherently restricted to structures already existing in nature, potentially limiting design flexibility for optimized cell differentiation or mechanical properties. Moreover, the texture analysis revealed that jackfruit-based constructs exhibited lower hardness and springiness compared to conventional pork and beef, indicating performance gaps in replicating meat mechanical properties.

The reliance on visual similarity metrics rather than comprehensive biomechanical validation reinforces the need for integrated assessment methods that evaluate both structural authenticity and functional performance. The strategies reviewed in this section (generative optimization, biomimetic replication, and natural screening) address different aspects of tissue replication. Future research should combine computational design, accurate tissue construction, and natural materials within hybrid methodologies, guided by standardized validation protocols that connect engineered constructs with consumer expectations.

3.4 Non-Invasive Monitoring and Quality Control

With production conditions and structures established, attention turns to process monitoring. While optimized media formulations and biomimetic scaffolds establish the conditions for cell growth and differentiation, translating these advances into reliable production systems requires continuous real-time monitoring. This represents a critical quality control challenge, as current invasive, endpoint-based assessment methods are unable to provide the timely data needed to ensure consistent performance. To overcome this, Udomsom et al. [46] developed automatic programmable bioreactors equipped with integrated sensor systems, demonstrating that hardware innovation is a prerequisite for effective AI deployment.

Building on this hardware foundation, AI-driven computer vision enables non-invasive cellular assessment at multiple scales. At the individual cell differentiation level, Yang et al. [47] developed a deep learning model capable of evaluating adipogenic differentiation in porcine cells using bright-field images ($R^2 = 0.83$), eliminating the need for destructive staining protocols that compromise sample viability. Extending this approach to more complex tissue constructs, Nabiullina et al. [48] fine-tuned a YOLO (You Only Look Once) neural network architecture to perform real-time object detection in 3D bioprinted structures. Critically, their model achieved high average precision in distinguishing between lipoblasts, fibroblasts, and myogenic cells within heterogeneous constructs, based solely on subtle morphological features in bright-field microscopy. Traditional classifiers cannot achieve this level of discrimination with unstained samples. This progression from single-cell differentiation monitoring to multi-cellular tissue analysis demonstrates the scalability of AI-driven quality control systems.

However, morphological monitoring alone cannot detect molecular-level risks that may compromise product safety without visible cellular changes. To address this critical gap, Shi et al. [49] introduced a multimodal deep learning framework that integrates Density Functional Theory calculations with mass spectrometry data. This approach allows computational toxicology to predict chemical hazards before they appear in the bioreactor. It enables high-throughput in silico screening of potential threats, including unexpected metabolites, cross-class toxins, and reactive intermediates, by modeling their molecular stability and reactivity dynamics. This level of detection prevents contamination events that morphological monitoring would only identify after significant batch compromise. Complementing chemical safety, AI-driven monitoring also addresses biosecurity risks inherent to cell-based production systems. Rzymski [50] argues that the risk of zoonotic disease transmission, such as avian influenza in conventional farming, provides additional rationale for cell-based production systems. In these systems, AI monitoring reinforces safety by eliminating pathogen exposure routes and reducing human handling errors. Collectively, these complementary monitoring modalities, including visual assessment of cellular identity [48], computational prediction of chemical hazards [49], biosecurity risk reduction [50], and hardware-level sensor integration [20,46], form a multi-scale safety architecture. This integrated monitoring framework aligns with the smart factory vision [26], where computer vision, predictive toxicology, and real-time sensor data provide closed-loop automation inputs, enabling adaptive process control that maintains product quality and safety across all production stages.

3.5 Consumer Intelligence and Digital Trust Systems

Technical production advances require parallel progress in market acceptance. The industrial feasibility of cultured meat is rendered obsolete without parallel advances in consumer acceptance. As emphasized by Hassoun et al. [51], the innovations of the fourth industrial revolution are fundamentally reshaping consumption patterns, yet multiple interconnected barriers impede adoption. While food neophobia and lack of familiarity constitute important psychological obstacles [52], comprehensive consumer surveys reveal a multifactorial pattern of consumer rejection. Health and safety concerns, sensory expectations regarding taste and texture, perceptions of unnaturalness, and economic factors represent equally, or more, significant acceptance barriers across diverse populations [53,54,55,56,57]. In this context, AI is being extended from bioprocess optimization to consumer intelligence applications. Consumer intelligence refers to the systematic AI-driven analysis of consumer preferences, psychological barriers, and behavioral patterns to inform targeted acceptance strategies. This approach can help identify and address these sociopsychological drivers.

To explore this complex landscape, AI-driven consumer intelligence operates across three complementary dimensions: understanding consumer preferences, detecting misinformation, and actively correcting it. First, Sun et al. [58] applied machine learning algorithms to conduct meta-analysis of consumer acceptance studies. Their approach identified non-linear determinants of willingnessto-pay, informing targeted product optimization such as the development of hybrid products to reduce the sensory gap [5,59]. Beyond consumer preferences, real-time misinformation detection has also become critical for market acceptance. Su et al. [60] utilized semi-supervised topic modeling, specifically Guided Latent Dirichlet Allocation, which integrates human expert insights. Applying this method to large-scale social media datasets, they classified consumer narratives into four dimensions: functional benefits, educational content, corporate social responsibility, and relational engagement. Their findings support the psychological barriers identified by Onwezen and Dagevos [52]. While narratives emphasizing functional benefits such as price and taste drive initial interest, educational content and relational engagement prove more effective at reducing the persistent neophobia surrounding high-tech foods. Translating these insights into active intervention, Ou et al. [61] demonstrated that high-expertise AI chatbots can improve credibility perceptions using two-sided corrective strategies. This approach acknowledges consumer concerns while providing evidence-based responses, allowing chatbots to function as automated educational agents. This progression from understanding preferences to detecting and actively correcting misinformation represents a promising AI-driven approach to consumer acceptance.

However, when skepticism stems from the perceived opacity of production processes, educational interventions alone are insufficient. Scientific evidence of safety and benefits, together with structural transparency measures, are required. Hassoun et al. [51] argue that perception of unnaturalness represents a fundamental barrier requiring structural transparency solutions. Addressing this, digital traceability systems that document the entire process, from cell sourcing to final product, can provide verifiable proof of safety and ethical standards, reducing concerns about artificial production methods [62]. Beyond building consumer trust, this transparency also opens new possibilities. The precise digital control of cellular agriculture allows personalized nutrition approaches, where AI integrates individual biological data (genomic profiles, health conditions) with 3D food printing technologies to tailor nutrient compositions, textures, and functional properties to specific consumer needs [51,63]. This capability is not achievable through conventional meat production, and could reframe the engineered nature of cultured meat as a functional advantage rather than a limitation.

Beyond transparency and personalization, emerging digital platforms allow consumer engagement with production processes. Hamad and Soni [64] describe how coupling digital traceability with interactive visual interfaces allows consumers to explore the entire production chain through virtual replicas of manufacturing facilities. This turns abstract production concepts into tangible, verifiable experiences. The convergence of transparency technologies, personalized nutrition, and immersive visualization represents the integration of fourth industrial revolution advances, such as AI, advanced manufacturing, and digital connectivity, into a cohesive consumer acceptance strategy. The AI-driven optimizations documented across media formulation, tissue architecture, quality control, and consumer intelligence address cultured meat's dual challenge: achieving technical feasibility while building consumer trust through transparency and personalized functional value not attainable through conventional production.

3.6 Critical Perspectives and Future Trends

Having examined individual technical domains, a critical synthesis of systemic challenges is warranted. This systematic review reveals a fundamental paradox. The AI technologies capable of optimizing cultured meat production require commercial-scale operational data that only economically viable facilities can generate. However, achieving such viability depends on these optimization systems already being functional. This circular dependency is the central challenge in this field, and it is often underestimated in individual studies that tend to focus on favorable results. For instance, Isaac et al. [34] demonstrated this limitation when machine learning classifiers for peptide bioactivity screening achieved area under the curve scores barely above 0.5 (equivalent to random classification), primarily due to insufficient training dataset sizes.

Key systemic constraints limit near-term commercial translation despite the technical advances documented across preceding sections. The literature's predominant focus on technical feasibility obscures economic and social realities. Humbird [16] performed a techno-economic analysis, concluding that production costs could exceed those of conventional meat by orders of magnitude, an issue that remains largely unaddressed by AI-focused studies. Moreover, the implementation of AI systems introduces additional costs, including computational infrastructure, data management, and specialized personnel. These costs remain largely unquantified and may result in sophisticated tools for processes that are not yet economically viable. Regulatory asymmetries present another critical constraint. GMO-based approaches offering theoretical advantages [33] face substantially more stringent approval pathways than non-GMO frameworks [32,35], yet the literature provides minimal strategic guidance for managing these divergent routes.

The absence of regulatory frameworks from the research ecosystem represents a fundamental gap. In addition, persistent misalignment exists between technical optimization priorities and consumer acceptance factors. While advances in production efficiency dominate research efforts, consumer acceptance depends on naturalness perceptions, safety confidence, and trust in production transparency [35,65]. The shift toward personalized nutrition documented in Section 3.5 is promising but requires validation through behavioral studies measuring actual consumption rather than stated preferences.

Reaching commercial viability requires two fundamental shifts: from isolated proof-of-concept demonstrations to integrated production systems, and from sustainability-focused narratives to personalized nutrition approaches that use cultured meat's unique capacity for digital control. Several developments are critical for this transition. Open data ecosystems through industry consortia can address data scarcity by enabling federated learning and pre-competitive data sharing while protecting commercial interests. This would reduce the knowledge silos that currently limit model generalizability. Hybrid validation methods that combine mechanistic modeling with data-driven AI and experimental confirmation at pilot-scale facilities provide the pathway for translating computational predictions into verified industrial performance. Finally, consumer co-development approaches that go beyond identifying barriers toward participatory design with long-term behavioral validation can align technical capabilities with actual market requirements. This would ensure that optimization priorities reflect real consumer acceptance factors rather than assumed preferences.

The question posed: "Is the time now?" requires realistic assessment. Current AI-driven cultured meat development demonstrates significant individual technical achievements but has not yet achieved the systemic integration, economic viability, regulatory clarity, and consumer acceptance required for commercial success. However, the combination of computational biology, advanced manufacturing, and consumer intelligence technologies creates new opportunities for acceleration. This review provides a foundational framework by synthesizing fragmented research domains, exposing critical tensions, and identifying strategic priorities. By providing critical synthesis of systemic challenges, this work offers researchers, policymakers, and industry stakeholders a roadmap emphasizing integration over isolation, economic reality over technical feasibility, and consumer alignment over production efficiency.

4. Conclusion

The convergence of AI and cellular agriculture represents a transformative opportunity to advance sustainable protein systems. This systematic review shows that while AI offers powerful tools across the cultured meat production pipeline, the path to commercial viability requires addressing systemic challenges that extend beyond computational advances.

Current achievements have not yet produced the economic viability, regulatory frameworks, or consumer trust necessary for imminent market success; however, AI-driven optimization is accelerating development timelines. In this context, cultured meat is positioned not as an immediate replacement for conventional meat production, but as a long-term alternative under active development.

This review has certain limitations. The literature search cutoff of December 2025 may exclude the latest developments in this rapidly evolving field. Additionally, the scarcity of commercial-scale operational data constrains the generalizability of current findings to industrial contexts.

These limitations notwithstanding, the integration of AI into cultured meat production remains a valuable research direction, provided that future efforts align technical progress with economic and regulatory viability.

Author Contributions

LM designed the research study. LM analyzed the data. LM prepared and wrote the manuscript. LM conducted the editorial revisions, approved the final manuscript, and takes responsibility for all aspects of the work.

Ethics Approval and Consent to Participate

Not applicable.

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Conflicts of Interest

The author declares no conflicts of interest.

Supplementary Material

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References

[1] United Nations, Department of Economic and Social Affairs, Population Division. World Population Prospects 2019: Highlights (ST/ESA/SER.A/423). United Nations. 2019.

[2] Food and Agriculture Organization of the United Nations. Pathways towards lower emissions: A global assessment of the greenhouse gas emissions and mitigation options from livestock agrifood systems. Food and Agriculture Organization of the United Nations. 2023. https://doi.org/10.4060/cc9029en

[3] Peyraud JL, Hocquette JF. Towards a balanced view of livestock: Benefits of grazing farming systems to produce meat. Livestock Science. 2025; 302: 105829. https://doi.org/10.1016/j.livsci.2025.105829

[4] Alcorta A, Porta A, Tárrega A, Alvarez MD, Vaquero MP. Foods for Plant-Based Diets: Challenges and Innovations. Foods (Basel, Switzerland). 2021; 10: 293. https://doi.org/10.3390/foods10020293

[5] Navarré A, Musto L, Nazareth T. Beyond Meat Substitution: A Multifaceted Review of Plant-Based and Alternative Proteins, from Environmental Impact to Analytical Technologies. Foods (Basel, Switzerland). 2025; 14: 2312. https://doi.org/10.3390/foods14132312

[6] Smetana S, Ristic D, Pleissner D, Tuomisto HL, Parniakov O, Heinz V. Meat substitutes: Resource demands and environmental footprints. Resources, Conservation, and Recycling. 2023; 190: 106831. https://doi.org/10.1016/j.resconrec.2022.106831

[7] Onwezen MC, Bouwman EP, Reinders MJ, Dagevos H. A systematic review on consumer acceptance of alternative proteins: Pulses, algae, insects, plant-based meat alternatives, and cultured meat. Appetite. 2021; 159: 105058. https://doi.org/10.1016/j.appet.2020.105058

[8] Gulzar S, Hosseini AF, Martín-Belloso O, Soliva-Fortuny R, Rizvi SSH. Engineering Processes for Plant-Based Meat Analogs: Current Status and Future Outlook. Comprehensive Reviews in Food Science and Food Safety. 2025; 24: e70322. https://doi.org/10.1111/1541-4337.70322

[9] Jang J, Lee DW. Advancements in plant based meat analogs enhancing sensory and nutritional attributes. NPJ Science of Food. 2024; 8: 50. https://doi.org/10.1038/s41538-024-00292-9

[10] Lee M, Park S, Choi B, Choi W, Lee H, Lee JM, et al. Cultured meat with enriched organoleptic properties by regulating cell differentiation. Nature Communications. 2024; 15: 77. https://doi.org/10.1038/s41467-023-44359-9

[11] Cornelissen K, Piqueras-Fiszman B. Consumers' perception of cultured meat relative to other meat alternatives and meat itself: A segmentation study. Journal of Food Science. 2023; 88: 91–105. https://doi.org/10.1111/1750-3841.16372

[12] Bryant C, Szejda K, Parekh N, Deshpande V, Tse B. A Survey of Consumer Perceptions of Plant-Based and Clean Meat in the USA, India, and China. Frontiers in Sustainable Food Systems. 2019; 3: 11. http://doi.org/10.3389/fsufs.2019.00011

[13] European Parliament and Council of the European Union. Regulation (EU) No 1308/2013 of the European Parliament and of the Council of 17 December 2013 establishing a common organisation of the markets in agricultural products. 2013. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32013R1308 (Accessed: 25 February 2026).

[14] European Parliament and Council of the European Union. Regulation (EU) 2015/2283 of the European Parliament and of the Council of 25 November 2015 on novel foods. 2015. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32015R2283 (Accessed: 25 February 2026).

[15] Food and Agriculture Organization of the United Nations. Cell based food and precision fermentation. 2023. Available at: https://www.fao.org/food-safety/scientific-advice/biotechnology--gmo-and-gm-foods/cell-based-food-and-precision-fermentation/cell-based-food-production-and-food-safety/en (Accessed: 25 February 2026).

[16] Humbird D. Scale-up economics for cultured meat. Biotechnology and Bioengineering. 2021; 118: 3239–3250. https://doi.org/10.1002/bit.27848

[17] Noble K, Huaccho Huatuco L, Dyke A, Green J. The Environmental Impacts of Cultured Meat Production. In Scholz SG, Howlett RJ, Setchi R (eds.) Sustainable Design and Manufacturing 2023 - Proceedings of the 10th International Conference on Sustainable Design and Manufacturing 2023 (pp. 91–101). Springer: Italy. 2024. http://doi.org/10.1007/978-981-99-8159-5_8

[18] Wang H, Fu T, Du Y, Gao W, Huang K, Liu Z, et al. Scientific discovery in the age of artificial intelligence. Nature. 2023; 620: 47–60. https://doi.org/10.1038/s41586-023-06221-2

[19] Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ (Clinical Research Ed.). 2021; 372: n71. https://doi.org/10.1136/bmj.n71

[20] Suychinov A, Akimova D, Kakimov A, Zharykbasov Y, Baikadamova A, Okuskhanova E, et al. Revolutionizing meat processing: A nexus of technological advancements, sustainability, and cultured meat evolution. Potravinarstvo Slovak Journal of Food Sciences. 2024, 18: 331–346. http://doi.org/10.5219/1957

[21] Hu Q. The contribution of artificial meat in reducing carbon emission and mitigating climate change. E3S Web of Conferences. 2025; 606: 03008. http://doi.org/10.1051/e3sconf/202560603008

[22] Ng WL, Tan JS. Machine Learning in Cultivated Meat: Enhancing Sustainability, Efficiency, Quality, and Scalability Across the Production Pipeline. Food and Bioprocess Technology. 2025; 18: 5988–6009. http://doi.org/10.1007/s11947-025-03853-2

[23] Todhunter ME, Jubair S, Verma R, Saqe R, Shen K, Duffy B. Artificial intelligence and machine learning applications for cultured meat. Frontiers in Artificial Intelligence. 2024; 7: 1424012. https://doi.org/10.3389/frai.2024.1424012

[24] Grzelak NL, Wu Y, Gadsden SA, Selvaganapathy PR. A smart automation platform for cultured meat advancement. SPIE Proceedings. 2025; 13484: 1348403. http://doi.org/10.1117/12.3051983

[25] Chiles RM, Broad G, Gagnon M, Negowetti N, Glenna L, Griffin MAM, et al. Democratizing ownership and participation in the 4th Industrial Revolution: challenges and opportunities in cellular agriculture. Agriculture and Human Values. 2021; 38: 943–961. https://doi.org/10.1007/s10460-021-10237-7

[26] Saraswat S, Bhargava T, Landge J, Tibrewal K. Towards intelligent cultivated/cultured meat factories: The synergy of AI, 3D bioprinting and automation in next-gen food manufacturing. Bioprinting. 2025; 51: e00441. http://doi.org/10.1016/j.bprint.2025.e00441

[27] Thirugnanasambandam MK, Pinto J, Moskovkina E, Costa RS, Oliveira R. A Physics-Informed Neural Network (PINN) framework for generic bioreactor modelling. Computers & Chemical Engineering. 2025; 203: 109354. http://doi.org/10.1016/j.compchemeng.2025.109354

[28] Catalão M, Pinto J, Torres CAV, Freitas F, Reis MAM, Costa RS, et al. Bioprocess model-predictive control with physics-informed neural networks: Driving microbiome evolution toward high polyhydroxyalkanoates production capacity. Journal of Process Control. 2025; 156: 103594. http://doi.org/10.1016/j.jprocont.2025.103594

[29] Rivera FJ, Chen J. Computational fluid dynamics modeling of cell cultures in bioreactors and its potential for cultivated meat production—A mini-review. Future Foods. 2022; 6: 100195. http://doi.org/10.1016/j.fufo.2022.100195

[30] Risner D, Negulescu P, Kim Y, Nguyen C, Siegel JB, Spang ES. Environmental Impacts of Cultured Meat: A Cradle-to-Gate Life Cycle Assessment. ACS Food Science & Technology. 2024; 5: 61–74. https://doi.org/10.1021/acsfoodscitech.4c00281

[31] Sinke P, Swartz E, Sanctorum H, van der Giesen C, Odegard I. Ex-ante life cycle assessment of commercial-scale cultivated meat production in 2030. The International Journal of Life Cycle Assessment. 2023; 28: 234–254. http://doi.org/10.1007/s11367-022-02128-8

[32] Nikkhah A, Rohani A, Zarei M, Kulkarni A, Batarseh FA, Blackstone NT, et al. Toward sustainable culture media: Using artificial intelligence to optimize reduced-serum formulations for cultivated meat. The Science of the Total Environment. 2023; 894: 164988. https://doi.org/10.1016/j.scitotenv.2023.164988

[33] Yin Z, Liu F, Zhang Z, Zhou J, Li J, Chen J, et al. Application of synthetic biology in the cultured meat production. Trends in Food Science & Technology. 2025; 165: 105363. http://doi.org/10.1016/j.tifs.2025.105363

[34] Isaac KS, Combe M, Potter G, Sokolenko S. Machine learning tools for peptide bioactivity evaluation - Implications for cell culture media optimization and the broader cultivated meat industry. Current Research in Food Science. 2024; 9: 100842. https://doi.org/10.1016/j.crfs.2024.100842

[35] Broucke K, Van Pamel E, Van Coillie E, Herman L, Van Royen G. Cultured meat and challenges ahead: A review on nutritional, technofunctional and sensorial properties, safety and legislation.

Meat Science. 2023; 195: 109006. https://doi.org/10.1016/j.meatsci.2022.109006

[36] Siddiqui SA, Khan S, Ullah Farooqi MQ, Singh P, Fernando I, Nagdalian A. Consumer behavior towards cultured meat: A review since 2014. Appetite. 2022; 179: 106314. https://doi.org/10.1016/j.appet.2022.106314

[37] Fraeye I, Kratka M, Vandenburgh H, Thorrez L. Sensorial and Nutritional Aspects of Cultured Meat in Comparison to Traditional Meat: Much to Be Inferred. Frontiers in Nutrition. 2020; 7: 35. https://doi.org/10.3389/fnut.2020.00035

[38] Olenic M, Thorrez L. Cultured meat production: What we know, what we don't know and what we should know. Italian Journal of Animal Science. 2023; 22: 749–753. https://doi.org/10.1080/1828051X.2023.2242702

[39] Purslow PP. Missing information on the link between cell death mechanisms and good eating quality in cultured myofoods. Trends in Food Science & Technology. 2024; 148: 104516. https://doi.org/10.1016/j.tifs.2024.104516

[40] Hocquette JF, Chriki S, Fournier D, Ellies-Oury MP. Review: Will "cultured meat" transform our food system towards more sustainability? Animal : an International Journal of Animal Bioscience. 2025; 19 Suppl 1: 101145. https://doi.org/10.1016/j.animal.2024.101145

[41] Heine S, Ahlfeld T, Albrecht FB, Gelinsky M, Kluger PJ. How biofabrication can accelerate cultured meat's path to market. Nature Reviews Materials. 2024; 9: 83–85. http://doi.org/10.1038/s41578-024-00650-9

[42] Li L, Zhang Y, Xu Z, Yan S, Yan N, Zhao C, et al. Engineering scaffold-cell interactions for cultured meat: Mechanisms, materials, and emerging AI-driven strategies. Trends in Food Science & Technology. 2025, 165: 105362. http://doi.org/10.1016/j.tifs.2025.105362

[43] Wu D, Pang S, Bäther S, Woelken L, Abyzova M, Morales-Dalmau J, et al. Embedded bioprinting enables precise fabrication of cultured meat with authentic structural properties. Food Hydrocolloids. 2026; 171: 111795. http://doi.org/10.1016/j.foodhyd.2025.111795

[44] Lanaro M, Mclaughlin MP, Simpson MJ, Buenzli PR, Wong CS, Allenby MC, et al. A quantitative analysis of cell bridging kinetics on a scaffold using computer vision algorithms. Acta Biomaterialia. 2021; 136: 429–440. https://doi.org/10.1016/j.actbio.2021.09.042

[45] Ong S, Loo L, Pang M, Tan R, Teng Y, Lou X, et al. Decompartmentalisation as a simple color manipulation of plant-based marbling meat alternatives. Biomaterials. 2021; 277: 121107. https://doi.org/10.1016/j.biomaterials.2021.121107

[46] Udomsom S, Budwong A, Wongsa C, Sangngam P, Baipaywad P, Manaspon C, et al. Automatic Programmable Bioreactor with pH Monitoring System for Tissue Engineering Application. Bioengineering (Basel, Switzerland). 2022; 9: 187. https://doi.org/10.3390/bioengineering9050187

[47] Yang L, Wu Z, Zhu H, Ding S, Zhou G. A method for evaluating the degree of Adipogenic differentiation of porcine cells cultured in suspension based on deep learning. Food Research International (Ottawa, Ont.). 2025; 212: 116324. https://doi.org/10.1016/j.foodres.2025.116324

[48] Nabiullina R, Golovin S, Kirichenko E, Petrushan M, Logvinov A, Kaplya M, et al. 3D Bioprinting of Cultivated Meat Followed by the Development of a Fine-Tuned YOLO Model for the Detection and Counting of Lipoblasts, Fibroblasts, and Myogenic Cells. Frontiers in Bioscience (Landmark Edition). 2025; 30: 36266. https://doi.org/10.31083/FBL36266

[49] Shi L, Jia W, Zhang R, Fan Z, Bian W, Mo H. High-throughput analysis of hazards in novel food based on the density functional theory and multimodal deep learning. Food Chemistry. 2024; 442: 138468. https://doi.org/10.1016/j.foodchem.2024.138468

[50] Rzymski P. Avian influenza outbreaks in domestic cats: another reason to consider slaughter-free cell-cultured poultry? Frontiers in Microbiology. 2023; 14: 1283361. https://doi.org/10.3389/fmicb.2023.1283361

[51] Hassoun A, Cropotova J, Trif M, Rusu AV, Bobiş O, Nayik GA, et al. Consumer acceptance of new food trends resulting from the fourth industrial revolution technologies: A narrative review of literature and future perspectives. Frontiers in Nutrition. 2022; 9: 972154. https://doi.org/10.3389/fnut.2022.972154

[52] Onwezen MC, Dagevos H. A meta-review of consumer behaviour studies on meat reduction and alternative protein acceptance. Food Quality and Preference. 2024; 114: 105067. http://doi.org/10.1016/j.foodqual.2023.105067

[53] Chriki S, Alhujaili A, Hallman WK, Payet V, Ellies-Oury MP, Hocquette JF. Attitudes toward artificial meat in Arab countries. Journal of Food Science. 2024; 89: 9711–9731. https://doi.org/10.1111/1750-3841.17559

[54] Bekker GA, Tobi H, Fischer ARH. Meet meat: An explorative study on meat and cultured meat as seen by Chinese, Ethiopians and Dutch. Appetite. 2017; 114: 82–92. https://doi.org/10.1016/j.appet.2017.03.009

[55] Chriki S, Payet V, Pflanzer SB, Ellies-Oury MP, Liu J, Hocquette É, et al. Brazilian Consumers' Attitudes towards So-Called "Cell-Based Meat". Foods (Basel, Switzerland). 2021; 10: 2588. https://doi.org/10.3390/foods10112588

[56] Rodríguez Escobar MI, Han S, Cadena E, De Smet S, Hung Y. Cross-cultural consumer acceptance of cultured meat: A comparative study in Belgium, Chile, and China. Food Quality and Preference. 2025; 127: 105454. https://doi.org/10.1016/j.foodqual.2025.105454

[57] Szejda K, Stumpe M, Raal L, Tapscott CE. South African Consumer Adoption of Plant-Based and Cultivated Meat: A Segmentation Study. Frontiers in Sustainable Food Systems. 2021; 5: 744199. https://doi.org/10.3389/fsufs.2021.744199

[58] Sun J, Caputo V, Taylor H. Using machine-learning methods in meta-analyses: An empirical application on consumer acceptance of meat alternatives. Applied Economic Perspectives and Policy. 2024; 46: 1506–1532. http://doi.org/10.1002/aepp.13446

[59] Hoek AC, Luning PA, Weijzen P, Engels W, Kok FJ, de Graaf C. Replacement of meat by meat substitutes. A survey on person- and product-related factors in consumer acceptance. Appetite. 2011; 56: 662–673. https://doi.org/10.1016/j.appet.2011.02.001

[60] Su LY-F, Chen T, Ng YMM, Gong Z, Wang Y-C. Integrating Human Insights Into Text Analysis: Semi-Supervised Topic Modeling of Emerging Food-Technology Businesses' Brand Communication on Social Media. Social Science Computer Review. 2024; 42: 416–437. http://doi.org/10.1177/08944393231184532

[61] Ou M, Ho SS, Wijaya SA. Harnessing AI to Address Misinformation on Cultivated Meat: The Impact of Chatbot Expertise and Correction Sidedness. Science Communication. 2025; 47: 859–896. http://doi.org/10.1177/10755470251315097

[62] Ahmadi Kaliji S, Pakseresht A, Hocquette JF. Can blockchain revolutionize meat production? Addressing transparency, trust, and compliance in conventional and cultured meat. Trends in Food Science & Technology. 2025; 163: 105197. https://doi.org/10.1016/j.tifs.2025.105197

[63] Bhuiyan MNI, Nahid M. Smart nutrition: AI and 3D printing for personalized diets. Food Nutrition. 2025; 1: 100032. http://doi.org/10.1016/j.fnutr.2025.100032

[64] Hamad AM, Soni R. Food in the Metaverse and Web 3.0 Era: Intersecting Food, Technology, and Culture. IGI Global Scientific Publishing. 2025. http://doi.org/10.4018/979-8-3693-9025-2

[65] Pakseresht A, Ahmadi Kaliji S, Canavari M. Review of factors affecting consumer acceptance of cultured meat. Appetite. 2022; 170: 105829. https://doi.org/10.1016/j.appet.2021.105829