

Global food security: Opportunities with cutting-edge technologies for ecological and healthy animal breeding

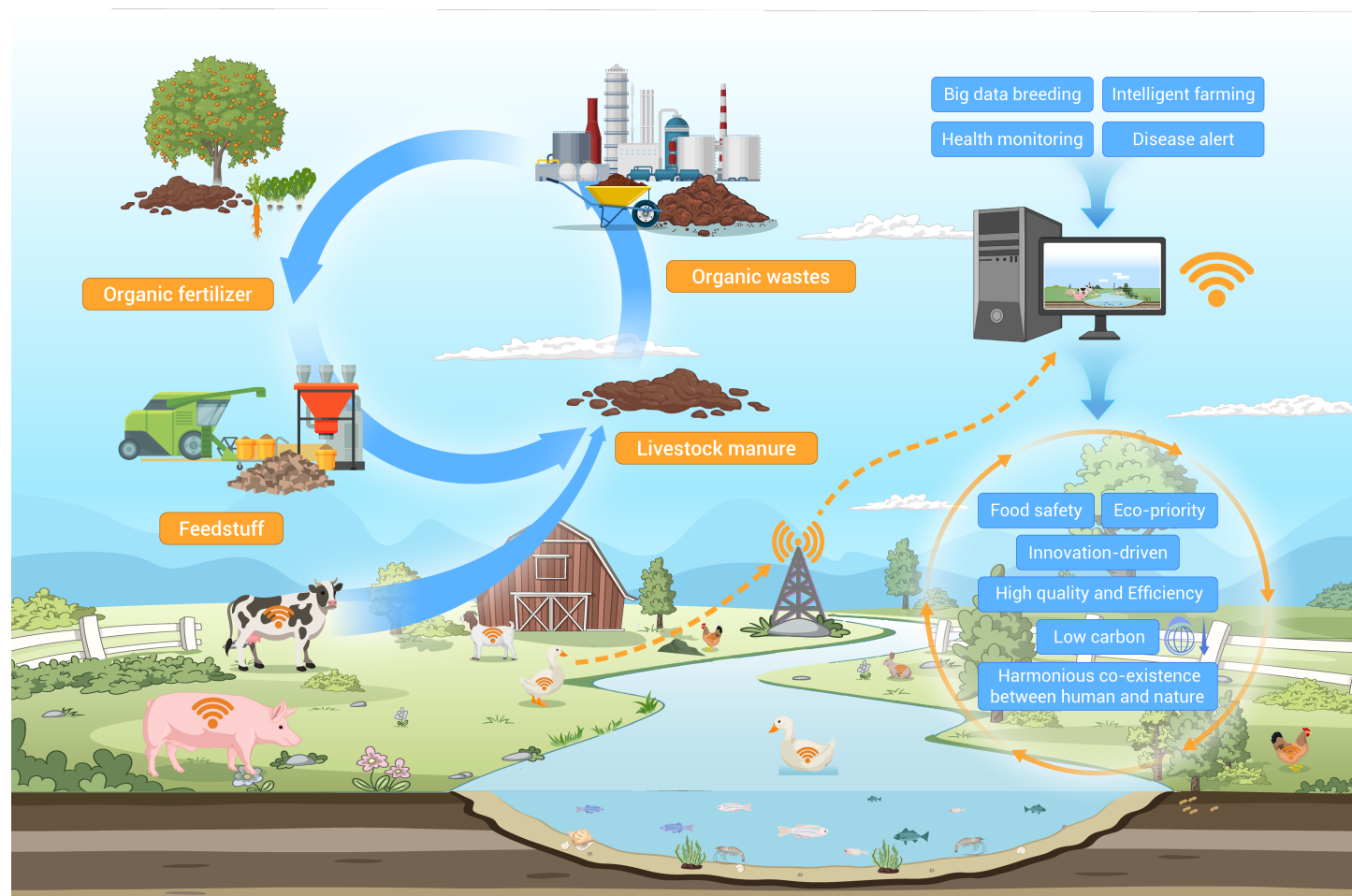
Fengna Li,^{1,43} Yehui Duan,^{1,43} Yuhua Fu,^{2,16,43} Qifeng Li,^{3,43} Qiuping Guo,¹ Xiumin Zhang,¹ Dan Wan,¹ Tianhai Yan,⁴ Lu Lu,⁵ Lei Zhou,⁶ Congjiao Sun,⁷ Lingyang Xu,⁸ Weimin Wang,⁹ Zhiquan Wang,¹⁰ Guosheng Su,¹¹ Xiaolei Liu,^{2,16} Kui Xu,¹ Feng Zhang,¹ Xiangfang Zeng,¹² Lianqiang Che,¹³ Na Dong,¹⁴ Shusong Wu,¹⁵ Lvhui Sun,^{2,16} Xiaoyun Su,¹⁷ Huiying Luo,¹⁷ Yanfen Cheng,¹⁸ Ifen Hung,¹⁹ Chunxue Liu,¹⁹ Sha Wei,²⁰ Mengmeng Han,¹ Qilong Li,¹ Fubin Yin,²⁰ Wanqin Zhang,²⁰ Shunli Wang,²⁰ Yue Wang,²⁰ Yunhao Zheng,²⁰ Hui Wang,¹⁷ Xiaoshuai Wang,²¹ Kaiying Wang,²¹ Qiumei Yang,²² Deqin Xiao,²² Hao Wang,²³ Shunlai Xu,²³ Longshen Liu,²⁴ Mingzhou Lu,²⁴ Yu Liu,^{25,26} Ligen Yu,³ Chaoyuan Wang,^{25,26} Wen Yao,²⁷ Peipei Yang,^{28,29} Xiao Yang,^{25,26} Zemeng Feng,¹ Xiangdong Sun,³⁰ Xiaowen Li,^{31,32} Shijie Ding,³³ Xiaonan Sui,³⁴ Qinhong Wang,³⁵ Xin Guan,³⁶ Jinchuang Zhang,³⁷ Ibeogu Isaiah Henry,³⁸ Hadiza Bako,³⁸ Changbo Tang,³⁸ Jie Wang,³⁸ Joshua E. Flack,³⁹ Mark J. Post,³⁹ Tianwei Wang,⁴⁰ Martin Nyachoti,⁴¹ Sung Woo Kim,⁴² Guanghong Zhou,³⁸ Md. Abul Kalam Azad,¹ Xiangfeng Kong,¹ Shuhong Zhao,^{2,16} Min Wang,^{1,*} Hongmin Dong,^{20,*} Liang Yang,^{17,*} Chunbao Li,^{38,*} and Yulong Yin^{1,*}

*Correspondence: mwang@isa.ac.cn (M.W.); donghongmin@caas.cn (H.M.D.); yangliang@caas.cn (L.Y.); chunbao.li@njau.edu.cn (C.B.L.); yinyulong@isa.ac.cn (Y.L.Y)

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GRAPHICAL ABSTRACT



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Fengna Li,^{1,4,3} Yehui Duan,^{1,4,3} Yuhua Fu,^{2,16,4,3} Qifeng Li,^{3,4,3} Qiuping Guo,¹ Xiumin Zhang,¹ Dan Wan,¹ Tianhai Yan,⁴ Lu Lu,⁵ Lei Zhou,⁶ Congjiao Sun,⁷ Lingyang Xu,⁸ Weimin Wang,⁹ Zhiquan Wang,¹⁰ Guosheng Su,¹¹ Xiaolei Liu,^{2,16} Kui Xu,¹ Feng Zhang,¹ Xiangfang Zeng,¹² Lianqiang Che,¹³ Na Dong,¹⁴ Shusong Wu,¹⁵ Lvhui Sun,^{2,16} Xiaoyun Su,¹⁷ Huiying Luo,¹⁷ Yanfen Cheng,¹⁸ Ifen Hung,¹⁹ Chunxue Liu,¹⁹ Sha Wei,²⁰ Mengmeng Han,¹ Qilong Li,¹ Fubin Yin,²⁰ Wanqin Zhang,²⁰ Shunli Wang,²⁰ Yue Wang,²⁰ Yunhao Zheng,²⁰ Hui Wang,¹⁷ Xiaoshuai Wang,²¹ Kaiying Wang,²¹ Qiumei Yang,²² Deqin Xiao,²² Hao Wang,²³ Shunlai Xu,²³ Longshen Liu,²⁴ Mingzhou Lu,²⁴ Yu Liu,^{25,26} Ligen Yu,³ Chaoyuan Wang,^{25,26} Wen Yao,²⁷ Peipei Yang,^{28,29} Xiao Yang,^{25,26} Zemeng Feng,¹ Xiangdong Sun,³⁰ Xiaowen Li,^{31,32} Shijie Ding,³³ Xiaonan Sui,³⁴ Qinhong Wang,³⁵ Xin Guan,³⁶ Jinchuang Zhang,³⁷ Ibeogu Isaiah Henry,³⁸ Hadiza Bako,³⁸ Changbo Tang,³⁸ Jie Wang,³⁸ Joshua E. Flack,³⁹ Mark J. Post,³⁹ Tianwei Wang,⁴⁰ Martin Nyachoti,⁴¹ Sung Woo Kim,⁴² Guanghong Zhou,³⁸ Md. Abul Kalam Azad,¹ Xiangfeng Kong,¹ Shuhong Zhao,^{2,16} Min Wang,^{1,*} Hongmin Dong,^{20,*} Liang Yang,^{17,*} Chunbao Li,^{38,*} and Yulong Yin^{1,*}

¹Institute of Subtropical Agriculture, Chinese Academy of Sciences, Changsha 410125, China

²College of Animal Science and Technology, Huazhong Agricultural University, Wuhan 430070, China

³Research Center of Information Technology, Beijing Academy of Agriculture and Forestry Sciences, Beijing 100097, China

⁴Agri-Food and Biosciences Institute, Hillsborough County Down BT26 6DR, UK

⁵Institute of Animal Genetics and Breeding, College of Animal Science and Technology, Sichuan Agricultural University, Chengdu 611130, China

⁶College of Veterinary Medicine, China Agricultural University, Beijing 100193, China

⁷Ministry of Agriculture and Rural Affairs, China Agricultural University, Beijing 100193, China

⁸State Key Laboratory of Animal Biotech Breeding, Institute of Animal Science, Chinese Academy of Agricultural Sciences, Beijing 100193, China

⁹College of Animal Science and Technology, Gansu Agricultural University, Lanzhou 730070, China

¹⁰Livestock Gentec, Department of Agricultural, Food and Nutritional Science, University of Alberta, Edmonton T6G 2P5, Canada

¹¹Center for Quantitative Genetics and Genomics, Aarhus University, Aarhus DK-8000, Denmark

¹²State Key Laboratory of Animal Nutrition, College of Animal Science and Technology, China Agricultural University, Beijing 100193, China

¹³Animal Nutrition Institute, Sichuan Agricultural University, Chengdu 611130, China

¹⁴The Laboratory of Molecular Nutrition and Immunity, College of Animal Science and Technology, Northeast Agricultural University, Harbin 150030, China

¹⁵College of Animal Science and Technology, Hunan Agricultural University, Changsha 410128, China

¹⁶Hubei Hongshan Laboratory, Wuhan 430070, China

¹⁷State Key Laboratory of Animal Nutrition and Feeding, Institute of Animal Science, Chinese Academy of Agricultural Sciences, Beijing 100193, China

¹⁸National Center for International Research on Animal Gut Nutrition, Nanjing Agricultural University, Nanjing 210095, China

¹⁹Anyou Biotechnology Group Co., LTD., Taicang 215437, China

²⁰Institute of Environment and Sustainable Development in Agriculture, Chinese Academy of Agricultural Sciences, Beijing 100081, China

²¹College of Biosystems Engineering and Food Science, Zhejiang University, Hangzhou 310058, China

²²College of Mathematics and Informatics, South China Agricultural University, Guangzhou 510642, China

²³Chongqing Academy of Animal Sciences, Chongqing 402460, China

²⁴College of Artificial Intelligence, Nanjing Agricultural University, Nanjing 210031, China

²⁵College of Water Resources and Civil Engineering, China Agricultural University, Beijing 100083, China

²⁶Key Laboratory of Agricultural Engineering in Structure and Environment, Ministry of Agriculture and Rural Affairs, Beijing 100083, China

²⁷College of Animal Science and Technology, Nanjing Agricultural University, Nanjing 210095, China

²⁸State Key Laboratory of Multimodal Artificial Intelligence Systems, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China

²⁹School of Artificial Intelligence, University of Chinese Academy of Sciences, Beijing 101408, China

³⁰China Animal Health & Epidemiology Center, Qingdao 266032, China

³¹New Hope Liuhe Co., Ltd, Chengdu 610023, China

³²Quality Control for Feed and Products of Livestock and Poultry Key Laboratory of Sichuan Province, Chengdu 610023, China

³³Nanjing Joes Future Food Technology Co., Ltd, Nanjing 211225, China

³⁴College of Food Science, Northeast Agricultural University, Harbin 150030, China

³⁵Tianjin Institute of Industrial Biotechnology, Chinese Academy of Science, Tianjin 300308, China

³⁶School of Biotechnology, Jiangnan University, Wuxi 214122, China

³⁷Institute of Food Science and Technology, Chinese Academy of Agricultural Sciences, Beijing 100193, China

³⁸State Key Laboratory of Meat Quality Control and Cultured Meat Development, MOST, Nanjing Agricultural University, Nanjing 210095, China

³⁹Mosa Meat B.V., Maastricht 6229 PM, The Netherlands

⁴⁰State Key Laboratory of Microbial Resources, Institute of Microbiology, Chinese Academy of Sciences, Beijing 100101, China

⁴¹Department of Animal Science, University of Manitoba, Winnipeg, Manitoba R3T2N2, Canada

⁴²Department of Animal Science, North Carolina State University, Raleigh NC 27695, USA

⁴³These authors contributed equally

*Correspondence: mwang@isa.ac.cn (M.W.); donghongmin@caas.cn (H.M.D.); yangliang@caas.cn (L.Y.); chunbao.li@njau.edu.cn (C.B.L.); yinyulong@isa.ac.cn (Y.L.Y)

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Food safety has been the concern of the global society, as an important link in the food supply chain, livestock and poultry breeding has a significant impact on it. With global population growth and dietary shifts, food demand is posing challenges in resource use, environmental impact, and disease risks for conventional livestock production. It is necessary to establish and promote the concept of ecological and healthy breeding, and ensure food safety from the perspective of the whole industry chain of livestock and

poultry. Therefore, this review focuses on the whole industry chain of livestock and poultry for the first time to elucidate the new technologies of ecological and healthy livestock breeding from six aspects, including new breeding technology, efficient utilization and substitution of nutrition, resource utilization of breeding waste, animal welfare, intelligent diagnosis and future food. While vertical integration enhances efficiency, rigid segmentation creates sustainability disconnects, as upstream innovations

often overlook mid/downstream impacts, leaving systemic challenges unaddressed. Therefore, the integration of these technologies fosters multidisciplinary collaboration across them. Future efforts should focus on optimizing these systems, expanding biobanks for alternative proteins, and strengthening global cooperation to balance human health and ecological resilience.

INTRODUCTION

Food security has emerged as a pivotal global concern, affecting not only individual health but also the well-being of society as a whole. Livestock and poultry breeding, as an important link in the food supply chain, plays a significant role in ensuring food security. Consumers now prioritize quality of life, demanding higher standards for food safety and intrinsic quality. This shift drives farmers to focus on how livestock and poultry breeding practices impact meat products, safeguarding consumer health.

The main targets in healthy livestock and poultry breeding include safety, quality, efficiency, and pollution reduction. Advances in animal and veterinary science and technology enable a favorable ecological environment for the rapid growth and development of livestock and poultry, supported by nutritionally balanced feed and reduced disease occurrence. These approaches also allow produce safe and healthy food for human beings. Therefore, successful animal farming requires multidisciplinary collaboration, including breeding, feed and nutrition, intelligent data management, disease monitoring, pollutant treatment and emission control, and artificial meat production. These technologies are not isolated but are interconnected to form a closed-loop ecological system. Specifically, intelligent data management optimizes feed and nutrition, which in turn minimizes waste and reduces pollutant emissions. This synergistic approach ensures that by-products from one segment are efficiently utilized or treated in another, thereby enhancing resource efficiency and safeguarding the entire production chain from farm to table.¹⁻⁴ Since food safety is closely linked to animal farming, strengthening the supervision and management of animal farming and controlling food production risks are essential. Therefore, it is necessary to establish and promote the concept of ecological and healthy breeding program and ensure food safety from the perspective of animal farming.

This review provides a comprehensive outline of the whole livestock and poultry industry chain, addressing the major needs for animal health and the quality and safety of meat, eggs, and milk products. This review also identifies solutions for the major technical and persistent challenges involved in food safety throughout this chain. Furthermore, it explores new technologies for ecological and healthy animal breeding from six key areas and takes healthy animal breeding as a systematic project to ensure food safety.

APPLICATION OF ADVANCED BREEDING TECHNOLOGY IN LIVESTOCK AND POULTRY PRODUCTION

The global demand for animal products is anticipated to increase by 70% by 2050. To meet this demand sustainably, implementing advanced technologies and strategies that can minimize environmental impact will be the key to maintaining and improving global food security.⁵ Among these, animal breeding technology stands out as one of the most effective methods for livestock and poultry production efficiency through genetic improvements. This approach enables the fulfillment of the growing demand for food, enhances product quality, and reduces environmental impact,^{5,6} critically providing tangible improvements to animal health and welfare (e.g., polled cattle, PRRS-resistant pigs). While traditional breeding requires long evaluation periods, the development of multi-omics technologies and advanced data analysis has introduced new tools. Breeding chips, genomic selection, genomic mating, and genome editing now offer powerful possibilities to accelerate genetic progress across this complex set of objectives—including traits for sustainability, welfare, and health (Figure 1).

Application of genomic breeding technology in pigs

Pigs are among the earliest domesticated farm animals and a pivotal source of meat production globally, particularly pork. Molecular marker-assisted selection (MAS) has revolutionized pig breeding by utilizing key genes; for instance, applying markers for genes like *IGF2* and *PRKAG3* has

significantly improved carcass quality and meat yield,⁷ while screening for the halothane gene has effectively eliminated the detrimental mutation responsible for porcine stress syndrome and PSE meat.⁸ These markers have refined breeding programs, enhancing overall productivity and meeting consumer demand for high-quality pork.

Genomic selection, a cutting-edge MAS method, utilizes genome-wide SNP markers and provides more accurate predictions than traditional methods.⁹ Recent research evidence showed that genotyping-by-sequencing could identify variants linked to important traits, such as birth weight¹⁰ and litter size,¹¹ providing valuable insights for genomic selection. Specialized breeding chips like "ZhongXin No. 1" and porcine 50K/80K liquid-phase chips offer guidance for genetic improvement through genomic selection.

Genomic mating optimizes economic value and performance in crossbred pigs whilst mitigating inbreeding depression.¹² It also effectively enhances production in commercial pigs, yielding highly efficient outcomes.¹³ However, genome mating's main limitation lies in its lack of inheritability. Conversely, the emerging technique of genome editing adds sustainable value, as it enables the creation of valuable genetic resources through cloning. Notable applications like the cytosine base editor (hA3A-BE3-NG)^{14,15} and somatic cell cloning for MSTN-edited Bama minipigs¹⁶ illustrate this potential for enhancing breeding. More significantly, the precise CRISPR/Cas9-mediated knockout of CD163 exon 7 yields pigs completely resistant to PRRSV¹⁷—a breakthrough that directly improves animal welfare, reduces antibiotic use and pathogen risks, and ultimately safeguards human health and food safety. By integrating molecular MAS, genomic selection, genomic mating, and genome editing, modern pig breeding is propelled into a new era of precision, efficiency, and sustainable advancement in the pork industry.

Application of genomic breeding technology in cattle

Cattle are immensely significant to humans as they serve as a primary source of meat and dairy products. Benefitting from MAS, researchers have identified a series of emerging genes associated with key economic traits in cattle. For meat production traits, genes such as *SIRT1*, *SIRT2*, *LPL*, *CRTC2*, and *MTPN* have been linked to body size and meat quality.¹⁸ Regarding dairy traits, *DOCK1*, *PTK2*, and *PIK3R1* have been shown to be associated with milk quality.¹⁹ These findings enable targeted breeding strategies for enhanced meat and dairy production.

Genomic selection in dairy cattle²⁰ has shown a 50% to 100% increase in the annual genetic gain of highly heritable traits and a 300% to 400% increase in low heritable traits.⁵ Crucially, these advancements extend to sustainability; for instance, by selecting for traits like improved feed efficiency and longevity, breeding programs are effectively reducing the carbon footprint per unit of milk produced.²¹ Advances in chip technologies, including variable SNP densities, combined with sophisticated prediction models (such as multi-trait²² and complex multi-breed²³ analyses) have further enhanced genomic selection efficiency and improved genetic progress.

In mating studies, various methods, including random mating and linear programming, have been used to control inbreeding and maximize genetic progress.²⁴ These approaches leveraged long-term beneficial effects in dairy bulls through exploring genomic information.²⁵ Additionally, incorporating dominance and heterozygosity effects in genomic mating can increase milk, fat, and protein yields,²⁶ while predictions from the Council on Dairy Cattle Breeding help avoid recessive genetic defects.²⁷

Genome editing in cattle exhibits solutions for disease resistance, altered milk composition, and improved animal welfare. For example, Cas9n-mediated *NRAMP1* insertion enhances tuberculosis resistance,²⁸ whereas precise editing in *CD18* creates Mannheimia haemolytica leukotoxin-resistant²⁹ cattle, and knockout in the β -lactoglobulin gene affects allergenic milk protein.³⁰ Additionally, introducing the Pc POLLED allele with transcription activator-like effector nuclease (TALEN) produces horn-free Holstein cattle.³¹ These research findings show the versatile applications of genome editing in advancing cattle traits, disease resistance, and animal welfare.

Application of genomic breeding technology in poultry

The chicken genome, sequenced in 2004 with approximately three million SNPs identified, paved the way for genomic breeding.³² Since then, the genome of several other poultry species, including the pigeon,³³ duck,³⁴ and



Figure 1. Knowledge (big data) driven genome design and breeding for sustainable livestock and poultry production The multi-omics approach integrates massive datasets to power advanced tools, including gene chip design, genomic selection, genome editing, and genomic mating. The application of these technologies moves beyond simply enhancing production efficiency to promote broader sustainability

goose³⁵ have also been sequenced. The application of high-density SNP arrays has accelerated the discovery of trait-associated genes. For instance, a previous study utilizing the Axiom® 600K high-density array identified a potential association between the *LRIG2* gene and beak deformity in affected birds.³⁶ Building on such discoveries, a key trend in breeding is to utilize these trait-associated loci to design more targeted, cost-effective commercial arrays. The "FengXin No.1" and "Jingxin No.1" 55K SNP chips are successful examples of this strategy. Meanwhile, liquid-phase chip technology based on sequence capture is emerging as a flexible and powerful new tool.

Genomic selection in poultry pure lines has significantly improved the breeding of laying hens, broilers, and domestic ducks. Single-step genomic BLUP outperforms conventional pedigree BLUP by 16% in predicting traits.³⁷ Additionally, genomic selection excels in predicting low heritability traits, such as residual feed intake³⁸ and disease resistance.³⁹ In commercial poultry production, multiline crossbreeding is used to transfer genetic traits from pure lines to commercial stocks.

The MAS in hybrid breeding has achieved notable successes, such as identifying the blue shell gene (*SLCO1B3*), which enables a 100% blue shell rate and the elimination of fishy odor carriers.⁴⁰ Primordial germ cell-based gene editing exhibits significant promise in chicken embryos despite challenges in gene editing due to age.⁴¹ This technology is already being applied to address critical welfare and disease challenges, thereby enhancing food safety and safeguarding human health. For example, editing the ANP32A gene to create chickens resistant to avian influenza.⁴² Moreover, the recent

completion of the world's first chicken genome sequence⁴³ is expected to significantly impact advanced gene editing and precision-designed molecular breeding in poultry.

Application of genomic breeding technology in sheep and goats

Sheep and goats contribute meat, wool, skin, and milk.⁴⁴ Several key genes, such as *FecB*, *CLPG*, and *MSTN*, are associated with prolificacy and muscle growth, which are applied in molecular MAS.⁴⁵ The *BMP2* and *PDGFD* genes influence tail shape and fat weight in sheep,⁴⁶ whereas *MUC6* associates with broad-spectrum adaptation in goats.⁴⁷

Since 2010, genome assembly and commercial SNP chips have facilitated large-scale reference populations for sheep and goats' genomic selection globally. Leading countries have made significant progress in this area. For instance, New Zealand has built a reference population of 26448 individuals (comprising Romney and other sheep),⁴⁸ and France maintains the world's largest dairy sheep reference herd with 4,800 Lacaune sheep.⁴⁹ Other nations like Australia, China, and the UK have also established their own extensive reference populations to accelerate genetic progress.^{48,50} In parallel with genomic efforts, distinct national breeding strategies, often involving crossbreeding, are prominent. For example, Australia is known for crossing Merino with Border Leicester sheep.⁵¹ Meanwhile, China focuses on improving high-fertility local breeds by incorporating specialized meat breeds such as the Australian White, Dorper, and Suffolk.

The UK pioneered sheep genome editing, producing double-musled sheep using TALEN technology.⁵² Afterward, the CRISPR/Cas9 system was used to

produce gene-edited sheep with enhanced traits such as litter size and muscle development. On the disease and welfare front, editing the PRNP gene to confer resistance to Scrapie represents a critical advancement for animal health and biosecurity.⁵³ Similarly, researchers at China Agricultural University and Xinjiang Academy of Animal Sciences developed short-tailed fine-wool sheep using the *T-box transcription factor T* gene editing.⁵⁴ With rapid advancements in technologies like big data and artificial intelligence,⁵⁵ sheep and goat breeding techniques are entering a new era.

Overall, current limitations in phenotyping technology, such as measuring total weight instead of specific tissue weights, lead to selecting indirect traits like backfat thickness. However, innovations in phenomics technology, including computer tomography (CT) for accurate *in vivo* measurements, could enable direct selection of carcass traits, thereby enhancing precision in breeding programs. Furthermore, advancements in Red-Green-Blue (RGB), RGB-Depth, hyperspectral, and other imaging technologies are generating massive, high-throughput data streams for livestock animals, such as pigs, cattle, sheep, and poultry, fueling the rise of data-driven phenomics.⁵⁶ By integrating this large-scale phenotypic data with genomic data, AI-assisted breeding technologies are poised for significant breakthroughs.⁵⁶ For example, recent advances include using deep learning and machine learning for more accurate genomic prediction of complex, low-heritability traits like climate resilience and disease resistance,⁵⁷ and applying computer vision to automatically extract novel behavioral or morphological phenotypes, such as lameness or feeding patterns.⁵⁸ These AI-driven approaches are creating the opportunity to truly bridge the gap between genomics and phenomics.⁵⁹ These integrated technologies not only save manpower but also improve biosecurity. It is important to note that animals are complex organisms, and while genetics are crucial in animal production, obtaining efficient meat, egg, and milk production also depends on optimal nutrition, environment, and management conditions to fully maximize the genetic potential.

EFFICIENT UTILIZATION AND SUBSTITUTION NUTRITIONAL TECHNOLOGIES: COST EFFECTIVE, EFFICIENCY ENHANCING, AND HIGH-QUALITY PRODUCT DEVELOPMENT

As mentioned above, genetic breeding facilitates the cultivation of food-producing animal breeds with better production performance, which is essential for sustainable livestock development. Notably, nutritional strategies play a vital role to achieve this goal. In the post-pandemic and anti-epidemic era, nutritional strategies have gained increased interest for improving animal growth performance, while cost-effective animal production remains a key challenge for the industry. This section explores core nutritional technologies to achieve the goals (Figure 2) discussed below, with the aim of achieving the balance point between sustainability, efficiency improvement, high quality, and cost reduction. Precision nutrition, which dynamically aligns nutrient supply with animal requirements, serves as a pivotal strategy for mitigating carbon and nitrogen emissions in livestock production. The implementation of these technologies directly enhances food safety and human health by fostering healthier animals, which in turn produce safer, higher-quality food products for consumers.

Reduction and replacement technologies for corn and soybean meal

Corn and soybean meal are the basic ingredients of pig and poultry diets, accounting for approximately 70% of total production costs.⁶⁰ Moreover, the continuous expansion of the pig and poultry industry has significantly increased the demand for energy and protein-rich feed ingredients. However, the fluctuating price and inconsistent supply of corn and soybean meal and their direct competition with human nutrition have become major challenges to the sustainability of feed and animal production.⁶¹ The growing global demand for sustainable animal nutrition has made alternative feed ingredients become an international priority, particularly as traditional crops like corn and soybean face supply constraints. In response, the Ministry of Agriculture and Rural Affairs of China initiated the "Plan for Reducing and Replacing Corn and Soybean Meal in Feed" in 2021, spurring interest in exploring alternative feed ingredients. Therefore, partial or complete replacement of corn and/or soybean meal partially or totally in animal feed has become a strategic objective for reducing production costs and contributing to sustainable animal

production.

Ideally, the use of alternative feedstuffs in diets must be both productively and economically efficient and should provide similar performance to that obtained from the feed it replaces. Emerging evidence has demonstrated that corn can be partially replaced by grain-based feeds,⁶²⁻⁶⁵ tubers, and their by-products.⁶⁶⁻⁶⁸ Concerning the substitution of soybean meal, high-protein alternatives include non-conventional sources such as leaf meals,⁶⁹⁻⁷¹ agricultural byproducts,⁷²⁻⁷⁴ and oilseed meals and related co-products.⁷⁵⁻⁷⁸ Other alternative protein sources include industrial by-products, macro- and micro-algae, insects, single-cell organisms, and high-protein corn.⁷⁹⁻⁸⁵ Nevertheless, numerous factors may interfere with or limit the use of alternative feedstuffs, including secondary plant metabolites, some of which have anti-nutritional effects. However, these substances can be reduced by using innovative feed technology, such as fermentation, enzymatic treatment, and the use of exogenous enzymes.⁸⁶

Apart from the corn and soybean meal replacement strategy, the low-protein diet has attracted considerable attention in animal production. Several studies on pigs have demonstrated the feasibility of reducing dietary protein by 2% to 6% compared to the levels recommended by NRC (2012).⁸⁷⁻⁹⁰ Optimal dietary protein for growing pigs weighing 7 to 110 kg exhibits a negative correlation with body weight, ranging from 18% to 12%.⁹¹⁻⁹³ Similarly, according to the group standard of "broiler and layer formulated feed", this also decrease across phases for both broilers and layers, suggesting that every 1% reduction in dietary protein level can lead to a corresponding 3% reduction in protein ingredient inclusion.⁹¹ Notably, to ensure that the growth performance remains unaffected, using the low protein diet strategy must not compromise the net energy requirement of pigs and poultry^{94,95} and should account for the appropriate ratio of digestible lysine to net energy,⁹⁶ the ideal ratio of limiting amino acid to lysine,⁹⁷ and the adequate mineral and electrolyte balance.⁹⁸

Nutritional regulation and efficient utilization technologies for key nutrients

The functionalization of ecological agricultural products involves applying precise nutrient enhancement technologies to improve nutritional quality and health benefits, such as producing selenium-enriched eggs and incorporating functional amino acids (AAs) to boost immune responses.⁹⁹ AAs have long been a key focus of animal nutritional research. By optimizing the optimal ratios and amounts of AAs in animal diets, animal nutritionists can formulate low-protein diets, reducing both protein content and feed costs.^{91,93,100-102} Currently, several crystalline AAs, such as lysine (Lys), methionine (Met), threonine (Thr), tryptophan (Trp), valine (Val), isoleucine (Ile), arginine (Arg), and histidine (His) are commonly used in low-protein diets. Concerning the perspectives of growth performance and meat quality, the optimal Leu:Ile:Val ratio in low-protein diets is recommended to be within the range from 1:0.25:0.25 to 1:0.75:0.75 for 10 to 30 kg pigs,¹⁰³ and 2:1:2 for 60 to 90 kg pigs.¹⁰⁴ Compared to normal-protein diets, low-protein diets supplemented with balanced Leu:Ile:Val ratios reduce soybean usage by 52% and 59% in 10 to 30 kg and 60 to 90 kg pigs without compromising growth performance. Apart from the formulation of low-protein diets, dietary supplementation with certain functional AAs, such as tryptophan,⁹⁶ glutamate,¹⁰⁵ and arginine,¹⁰⁶ can provide additional benefits, including enhanced meat quality, increased muscle gain, and reduced oxidative stress.

Similar to AAs, balanced fatty acids have a significant impact on animal growth efficiency and product quality. The two key fatty acid balances are the ratio of unsaturated fatty acids (UFA) to saturated fatty acids (SFA) and the ratio of n-6 to n-3 polyunsaturated fatty acids (PUFA). The UFA:SFA ratio in diets directly affects lipid digestibility and peroxidation. The average fat digestibility ranges from 85% to 92%. Fat digestibility rises when the UFA:SFA ratio is > 1.5 and declines when the ratio is less than 1.3.¹⁰⁷ Moreover, an optimal n-6:n-3 PUFA ratio in diets is also crucial for maintaining adequate growth and development in pigs and poultry, as well as for human health. For example, in weaned pigs, reducing the dietary n-6:n-3 PUFA ratio to 4:1 attenuated the inflammatory responses induced by poor sanitary conditions.¹⁰⁸ In growing pigs and sows, maintaining a n-6:n-3 PUFA ratio between 1:1 and 5:1 exerted beneficial effects on lipid metabolism, inflammatory system, and absorption and utilization of amino acids and fatty acids,

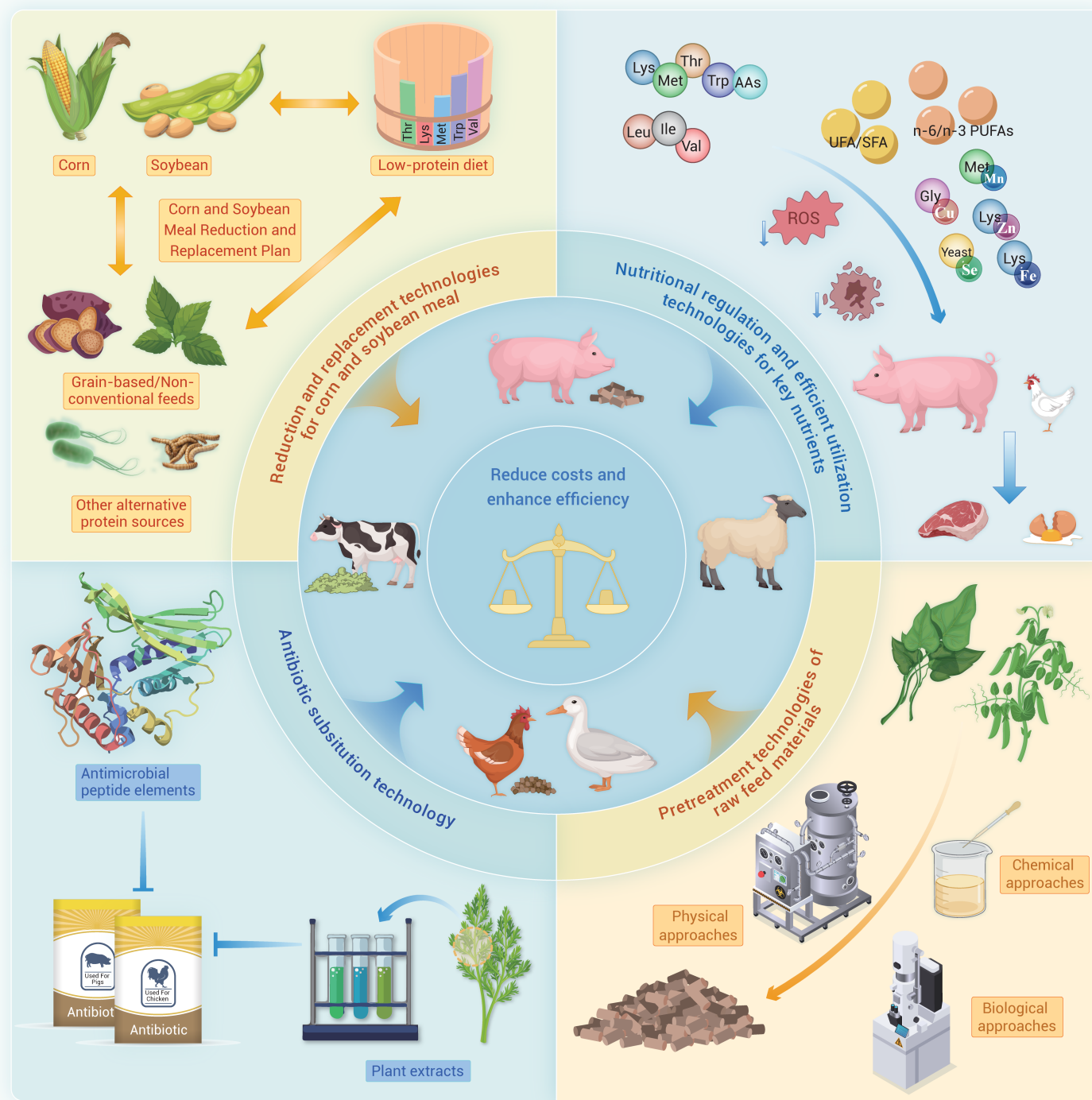


Figure 2. Efficient utilization of nutrients technologies in improving animal production and saving feed resources.

thereby resulting in the availability of more energy and nutrients for high performance, meat quality, and reproductive outcomes.¹⁰⁹⁻¹¹¹ In laying hens, the n-6/n-3 PUFA ratio at 5.5:1 optimized egg quality by enhancing immune responses and increasing n-3 PUFA deposition in the yolk.¹¹² Therefore, maintaining an optimal ratio of n-6 and n-3 PUFAs is essential for animal health and product quality. The functionalization of ecological agricultural products involves applying precise nutrient enhancement technologies to improve nutritional quality and health benefits, such as producing selenium-enriched eggs and incorporating functional amino acids to boost immune responses.

Mineral deficiencies, such as iron, zinc, and selenium, often lead to nutritional deficiency disorders, resulting in economic losses in livestock and poultry production. Exploring new organic chelates or synergies combinations with other nutrients could improve the bioavailability of trace minerals

and increase their enrichments in meat products, thereby benefiting consumers' health by overcoming chronic imbalances in trace element supply. Research evidence has shown that ingesting iron-enriched foods alongside vitamin C, folic acid, and/or oligosaccharides enhances iron deposition.¹¹³ Feeding organic iron, such as ferrous bis-glycinate, significantly improves iron status and serum lipid metabolism, enhances intestinal antioxidant capacity, and modulates gut microbiota and bile acid profiles in pigs.¹¹⁴ For zinc, replacing 50% to 100% inorganic ZnSO₄ with organic zinc like ZnMet, ZnGly, and Zn-propionate could improve carcass traits and zinc deposition in broiler chicken meat.¹¹⁵ In addition, selenium exerts potential biological functions through its incorporation into selenoproteins as selenocysteine.¹¹⁶ Commonly, sodium selenite, sodium selenate, nano-selenium, seleno-yeast, selenomethionine, and hydroxy-selenomethionine are the main sources of selenium used as feed additives for animals.^{117,118} Selenomethionine and

hydroxy-selenomethionine exhibit higher bioavailability than other selenium sources, which can improve the selenium content in animal products.¹¹⁷ It is well established that selenomethionine and its sulfur homolog can nonspecifically be incorporated into proteins in the place of methionine.¹¹⁷

The antibiotic substitution technology

The growing awareness of antimicrobial resistance and its impact on animal and human health has gained increasing interest to develop reliable alternatives to antibiotics, which is imperative. At present, plant extracts and antimicrobial peptides (AMPs) are potential alternatives to antibiotics.

Plant extracts exert a wide range of health-promoting effects, particularly oxidative and anti-inflammatory capacities. For instance, protocatechuic acid and vanillic acid in plant extracts can protect against oxidative stress and inflammation and improve barrier function in LPS-challenged pigs. Additionally, vanillic acid has been found to increase body weight by 7% at 21 days after weaning.^{119,120} Similar growth-promoting and anti-inflammatory effects have also been observed in growing-finishing pigs¹²¹ and gestating sows.^{122,123} Furthermore, plant extracts can enhance the quality of livestock products. For example, supplementing growing-finishing pigs with ethanol extract of mango seeds enriched in polyphenolic compounds reduced cooking loss while increasing non-protein sulphhydryl groups, phenolic compounds, and total antioxidant activity in the loin.¹²⁴ Dietary resveratrol supplementation has been shown to increase the intramuscular fat content in the *longissimus dorsi* muscles of growing-finishing pigs,¹²⁵ improving the flavor and color of pork. Moreover, plant extracts can disrupt quorum sensing systems to suppress virulence factor expression and biofilm formation in pathogenic bacteria,¹²⁶ thereby demonstrating potential as antibiotic alternatives in animal husbandry.

Similar to plant extracts, AMPs have exhibited beneficial anti-inflammatory effects in livestock and poultry. For example, dietary Microcin C7 supplementation has been shown to reduce the incidence of diarrhea, improve growth performance, and protect against intestinal barrier inflammation and microbial dysregulation in weaned piglets.¹²⁷ Additionally, intraperitoneal injection of 0.6 mg/kg AMPs cathelicidin-BF lowered serum levels of IL-6, IL-8, IL-10, TNF- α , TGF- β while increasing immunoglobulin IgA of piglets with diarrhea.¹²⁸ Similarly, in another study, the intraperitoneal injection of 0.6 mg/kg AMPs KR-32 alleviated intestinal inflammation, enhanced intestinal mucosal barrier function, and improved diarrhea status in weaning piglets.¹²⁹ Other synthetic AMPs, such as A3 and P5, have also been tested in weaning piglets, showing potential to improve growth performance, nutrient digestibility, and intestinal morphology, whilst reducing pathogenic bacteria.¹³⁰⁻¹³³ Overall, AMPs serve as an alternative to antibiotics, offering a promising path toward healthy farming due to their high efficiency, safety, and resistance to pathogens. However, most laboratory-produced AMPs rely on costly chemical synthesis, making them impractical for feed additive applications. Therefore, genetic engineering methods can enable cost-effective, large-scale AMP production, which might be the greatest promise for future agricultural applications of AMPs.

Pretreatment technologies of raw feed materials

To minimize anti-nutritional factors such as trypsin inhibitors, glycinine, lectin, tannin, glucosinolates, and toxic agents, as well as the breakdown of cellulose-, xylan- and lignin-rich plant cell walls, appropriate processing technologies and dietary formulation schemes are essentials. Advanced processing methods, including physical, chemical, and biological approaches, can maximize the utilization of non-conventional feed resources for animal production.¹³⁰⁻¹³³ Among these, physical methods include crushing, soaking, expansion, puffing, microwave, etc., whereas chemical methods involve ammonization, basification, etc. and biological methods include microbial fermentation, enzymatic hydrolysis, bacteria and enzymes synergism, etc.¹³⁰⁻¹³³ For flexible dietary formulation technologies, the nutritionists need to be familiar with the nutritional characteristics and evaluate the nutritional values of unconventional feed materials for formulation of diets.¹³⁴

The application of non-conventional feed materials through optimized processing methods and combination with feed formulation technology has achieved remarkable progress, such as the maintenance of comparable growth performance and animal health, when compared to the conventional

dietary structure.¹³⁴ Notably, combining multiple pretreatments can overcome the limitations of a single pretreatment method. Therefore, further research is necessary to balance between cost-effectiveness, practical on-farm applicability, and environmental impact of these pretreatments in livestock and poultry feeding. Further, the bioconversion of carbon dioxide into starch and protein, coupled with the cultivation and utilization of high-protein and high-oil crops, is driving a paradigm shift from resources dependence practices toward biomanufacturing-based approaches in the feed industry.

UTILIZATION TECHNOLOGIES OF LIVESTOCK AND POULTRY WASTE RESOURCES

With the rapid development of livestock and poultry industries in China, animal manure production has reached 3.8 billion tons. Additionally, livestock and poultry farming emitted about 10 million tons of chemical oxygen demand, accounting for 94% of total emission from agricultural emissions. It is worth mentioning that the concept of waste treatment and utilization follows a unified framework, encompassing source reduction, process control, and end-use to balance environmental and economic benefits. To ensure the sustainable development of the agricultural industry, it is urgent to address pollution and health risks while maximizing the efficient use of agricultural waste resources (Figure 3).

Coupling of crop and livestock systems and safe utilization

Coupling of crop and livestock systems to promote green development.

The expansion of livestock production and increasing specialization have resulted in the decoupling of crop and livestock production systems¹³⁵ and a reduction in manure use efficiency, which contributes to the greenhouse effect, eutrophication, acidification, and biodiversity loss.¹³⁶⁻¹³⁹ Therefore, reintegrating crop and livestock systems scientifically and effectively is crucial for achieving the sustainable development goals.

The advantages of integrated crop and livestock systems include better buffering against climate fluctuations, higher nutrient recycling through more direct soil-crop-animal manure relationships, more diversified income sources, and alternative uses for low-quality roughage.¹⁴⁰⁻¹⁴² The coupling of animal and crop production systems may significantly reduce nutrient loss to the environment and increase nutrient use efficiency; however, this integration needs to consider the whole life chain, including carbon footprint, nitrogen footprint, and water footprint^{143,144} and trade-offs between environmental impacts.² Effective implementation requires regional assessments of the spatial of cropping and livestock farms, matching manure production with nutrient absorption capacity, and simultaneous consideration of food safety requirements.¹⁴⁵

Moreover, the collaboration of stakeholders, including scientists, industry representatives, farmers, educators, and policymakers, from different sectors is necessary to maximize the benefits of integrated crop and livestock systems. Farmers are the key actors who manage land and livestock, and their management practices can be influenced by technology transfer, operational mechanisms, and public policy. The implementation of new technologies developed by scientists and new products introduced by industries requires policy support, as farmers may not adopt these technologies due to economic constraints. Therefore, a strong linkage must be established among stakeholders to accelerate technology innovation, transfer and application.

Digital and intelligent integrated crop and livestock system. Digital livestock production management is a complex engineering system integrating multidisciplinary theories and technologies. Establishing a comprehensive intelligent monitoring network and supporting equipment is crucial for maximizing the benefits of the scientific coupling of crop and livestock systems, as well as for evaluating the effectiveness of environmental protection measures. The monitoring system covers three key areas: large-scale farms, professional institutions for recycling livestock manure, and manure application fields. The monitoring links include feed input, on-farm manure storage and treatment, manure transport, and field application. At the farm level, smart meters can monitor total water, electricity, and manure consumption throughout the entire manure production chain. Self-propelled precision spreader equipment and intelligent feeding stations can implement quantitative feed input, ETC automatic weighing equipment can monitor animal

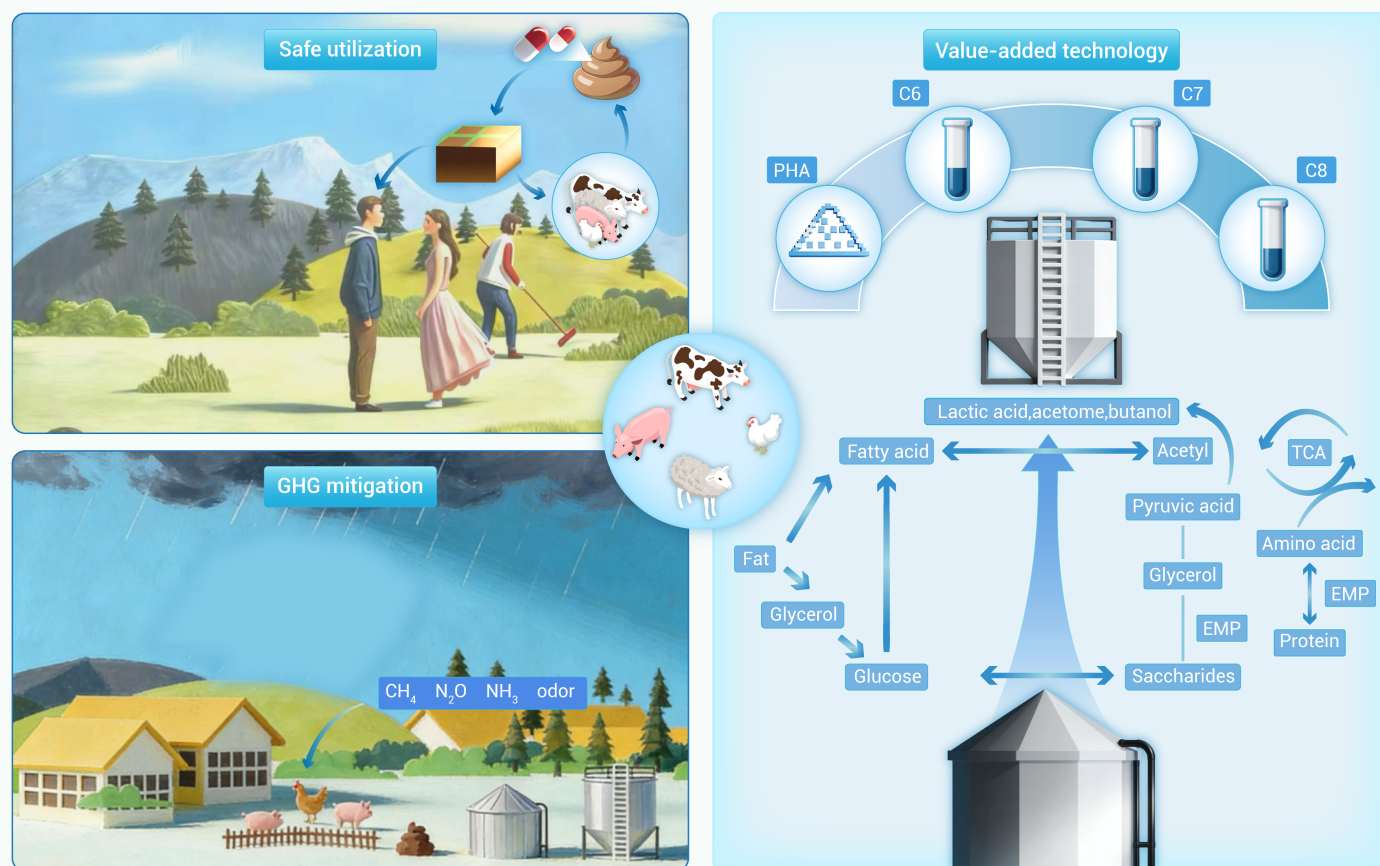


Figure 3. Main value-added pathways and GHG mitigation for livestock and poultry manure.

weight in real time. Additionally, Unmanned Aerial Vehicle (UAV) and digital operation recorders can supervise and control the manure application plot and slope of the plot, record manure application time, map the actual manure application plot area with GIS, application distribution uniformity, crop length of the applied plot, etc. These measures are integrated into cloud-based systems, enabling real-time remote monitoring through managers' computers, smartphones, and other devices. At the national level, existing national monitoring programs to evaluate surface ammonia concentrations include the Chinese Nationwide Nitrogen Deposition Monitoring Network established in 2010,¹⁴⁶⁻¹⁴⁸ the Ammonia Monitoring Network in China,¹⁴⁹ the Ammonia Monitoring Network in the US as well as the European Monitoring and Evaluation Programme.¹⁵⁰

Removal of antibiotic residue in livestock and poultry manure. Although antibiotics are completely prohibited in animal feed; however, their use remains permitted for treating animal diseases. The antibiotics are not completely absorbed in the animal's metabolism process, leading to certain amounts being excreted in livestock and poultry manure that poses a serious health risk to the environment and human. The reduction of antibiotic residues gives rise to a virtuous cycle interconnecting food safety, human health, and animal welfare. By mitigating public health risks like antimicrobial resistance and driving advancements in husbandry from improved habitats to preventive healthcare, this paradigm inherently raises animal welfare benchmarks, thereby securing safer food, healthier populations, and more ethically responsible production. Several common manure treatment methods, including anaerobic digestion, storage in ponds, and composting, can mitigate antibiotic residues in manure.

Antibiotics are more easily degraded by methanogenic microorganisms than by acidogenic microorganisms during the anaerobic digestion (AD) process, making microbial antibiotic degradation a valuable mechanism.¹⁵¹ A two-stage AD system could serve as an effective alternative for treating manure containing antibiotics, thereby minimizing their adverse effects on fermentation performance. For example, A two-stage AD system demon-

strated effective removal of common antibiotics, with elimination rates increasing substantially from the acidogenic to the methanogenic stage for both chlortetracycline (CTC) and oxytetracycline (OTC).¹⁵² In addition, antibiotic toxicity was reduced in the first stage, preventing methanogens in the second stage from being inhibited by residual antibiotics. Storage in ponds is a primary and cost-effective method for treating livestock slurry. The three-chamber anaerobic storage pond not only effectively prevents sludge cross-contamination but also significantly removes chlortetracycline, oxytetracycline, and tetracycline under moderate temperature conditions of 13-19°C.¹⁵³ Composting, another common manure treatment method, is also highly effective for removing antibiotics.¹⁵⁴

Value-added utilization technology of livestock and poultry manure

Bioconversion of animal manure into carboxylates. The AD system for biogas production is a well-established manure treatment method. However, as the economic value of biogas is limited, researchers are exploring alternative processes that yield higher-value end-products, such as carboxylic acids.¹⁵⁵ Short-chain carboxylic acids (SCCAs), including volatile fatty acids (VFAs) and lactic acid (LA), are versatile chemicals used in pharmaceuticals, cosmetics, textiles and as precursors for biofuels and biodegradable plastics, including polyhydroxyalkanoates (PHAs) and polylactic acid (PLA).¹⁵⁶ However, the complete miscibility of SCCAs renders the subsequent product separation and extraction process energetically costly.¹⁵⁷ In the industrial production of citric acid, downstream recovery alone accounts for 30 to 40% of the production cost.¹⁵⁸

Medium-chain carboxylic acids (MCCAs), containing 6 to 12 carbon atoms, exhibit lower hydrophobicity than SCCAs, but can be produced from SCCAs through chain elongation technology. Moreover, MCCAs exhibit higher energy density and stronger hydrophobicity than SCCAs.¹⁵⁹ MCCAs can be directly utilized as antimicrobial agents, food additives, and versatile platform chemicals.

To date, ethanol and lactate have been identified as the most ideal electron donors for driving the chain elongation process.^{157,160} A two-stage co-fermen-

tation system using swine manure and corn stalk silage, without external electron donors, realized a stable MCCAs production and overcame high electron donor costs.¹⁶¹ In addition, real-time MCCAs separation can be achieved by connecting the reactor to a separation system.¹⁶² The key issue now is to improve technologies focused on substrate pretreatment and the development of high-efficiency microbiomes. These advancements, combined with yield- and purity-enhancing strategies, are vital for achieving economical MCCAs production.

Biodegradable plastic-PHA production. The PHAs are a group of environment-friendly polyesters produced by various microorganisms under specific growth conditions with an imbalanced nutrient supply, they can be quickly biodegraded under different environments.¹⁶³ However, their higher production cost often restricts large-scale commercial production. The PHA production cost is mainly related to feedstock, PHA productivity during fermentation, and PHA extraction processes, among which feedstock accounts for 30 to 40% of the total production cost.^{164,165} The use of inexpensive feedstock for PHA production could substantially reduce the total production cost and considerably improve the marketability of PHA products, while also potentially mitigating the carbon emissions from the plastic production. Organic wastes discharged from animal husbandry, mainly involving manure, wastewater are the potential cost-effective carbon sources for PHA production.

A three-stage fermentation system is commonly employed to produce polyhydroxyalkanoates (PHAs) from animal husbandry wastes. These wastes are converted into lower molecules intermediates, and then synthesized to PHA by acclimated mixed microbial cultures (MMCs).^{166,167} In the biosynthesis pathway of PHA in MMCs, the even VFA and lactic acid can be firstly converted to acetyl-CoA or acetoacetyl-CoA, and then further PHB. Propionic acid can be converted to propionyl-CoA, acetyl-CoA, propionyl-CoA to produce PHV, or converted to acetyl-CoA before forming PHB. Following this strategy, dairy manure was hydrolyzed into VFAs and then synthesized into PHA by MMCs under aerobic conditions, yielding 22 kg PHA/kg of dairy manure (dry base).^{166,169} Bio-oil obtained from the fast pyrolysis of chicken beds was used to produce PHA by MMCs, achieving a 9.2% PHBV content in the dry cell weight.¹⁶⁹ Moreover, fatty acids derived from animal byproducts yielded 0.1 to 0.4 g PHA/g fatty acids.¹⁷⁰ Hydrolysates of rendering wastes were also used as nitrogen and carbon sources for PHA production.¹⁷¹ Nevertheless, there are still some technical challenges that need to be overcome to achieve high yield production of PHA. Main efforts can be contributed to choosing suitable feedstock, improving the productivity of PHA synthesis, and increasing the stability of PHA microorganism consortia in MMCs.^{167,172}

Protein production from animal manure. To realize the nutrient recovery of animal manure, insects were used to process manures and achieve protein recovery.¹⁷³ Black soldier fly (BSF) can ingest manure nutrients from and convert them into larval biomass, which serves as a valuable source of insect protein. Black soldier fly larvae (BSFL), rich in protein and lipids, can substitute fish and soybean meals in animal feed or be used for biodiesel production. However, like other insects, environmental factors may affect the protein content during BSFL growth.^{174,175} Therefore, optimizing the diet for BSFL's throughout its lifecycle is crucial for enhancing manure bioconversion and maximizing biomass yield.^{176,177}

The efficacy of BSF in converting animal manure to protein depends on multiple factors, including temperature, moisture, feed quality, light intensity, and feeding rate, which are critical for their larval growth, survival, and bioconversion performance.^{178,179} For example, BSFL fed with dairy manure exhibited slower growth and a lower survival rate than those fed with swine and chicken manure.¹⁸⁰ A diet of low-protein, high-carbohydrate substrates promotes lipid accumulation in BSFL, while protein-rich diets enhance their protein content, mass weight, and feed conversion ratio.^{181,182} Moreover, increasing the feeding rate can further accelerate the growth rate and biomass yield of BSFL. Therefore, optimizing environmental factors and feeding strategies can improve BSF's potential for large-scale production, offering a low-cost protein source for animal diets.

Pollution control and carbon reduction technology

Greenhouse Gas (GHG) mitigation technologies from manure management. Animal manure is utilized in renewable energy production, carbon

sequestration, and emission mitigation as a key strategy for achieving carbon neutrality in agricultural and waste valorization systems.¹⁸³ For ruminants, CH₄ production during enteric fermentation process is a major global concern. Host gene-microbiome interactions during rumen methanogenesis.^{184,185} Common feed additives used to reduce enteric CH₄ emissions include dietary lipids, ionophores, electron receptors, inhibitors, and plant bioactive compounds.^{185,186} Among these, promising enteric CH₄ inhibitors include 3-nitrooxypropanol and algae, which contain significant amounts of brominated halomethane bromoform; however, more research is needed to determine the most effective doses of these inhibitors. Electron receptors have shown potential to reduce enteric CH₄ emissions. However, improper administration of nitrate may negatively affect animal productivity. In addition, lowering the feed conversion ratio can further reduce CH₄ emissions by shifting ruminal fermentation patterns from acetate to propionate and lowering ruminal pH.

Liquid manure management systems, which often occur in anaerobic environments, are widely used in intensive livestock production operations and represent a major source of CH₄ emissions. Solid-liquid separation technology can decrease volatile solids content in manure, thereby decreasing anaerobic fermentation of organic matter and subsequent CH₄ emissions. Replacing deep-pit manure storage with solid-liquid separation systems can reduce GHG emissions by up to 60%.¹⁸⁷ While bio-filters can effectively oxidize CH₄ animal house exhaust air, they may also trigger N₂O emissions through nitrification of ammonia (NH₃).

Liquid manure is typically stored in lagoons or slurry ponds, which have high methane conversion factors (MCFs).¹⁸⁸ Covering lagoons or slurry ponds, for example with plastic covers, helps prevent gas emissions. Recent development of new cover materials, such as floating hexagonal blocks and floating balls that automatically assemble when dispersed on the slurry surface. Acidifying slurry to a pH below 6.0 inhibits methanogens and also nitrogen-transforming microbes, thereby effectively reducing both CH₄ and N₂O emissions.¹⁸⁹ Recently, a promising new bio-acidification approach involves inducing lactic acid production in stored slurry through the addition of carbon-rich organic matter, which significantly reduces GHG emissions from slurry storage.¹⁹⁰

For solid manure management, composting is an effective way to convert manure into organic fertilizer. However, traditional windrow composting often lead to high N₂O emissions due to anaerobic conditions. The advanced in-vessel composting system and the membrane-covered composting system can reduce CH₄ and N₂O emissions because of the dual mechanism: inhibiting GHG formation and blocking their emissions.¹⁹¹ In addition, adding super-phosphate and forsterite helps struvite crystals formation in the compost, thereby reducing N loss and N₂O emissions.

Control strategies of gaseous pollutants. Gaseous pollutants from livestock farms significantly impact both the ecological environment and the biological safety of animal production.¹⁹² These pollutants mainly include odors, NH₃, volatile organic compounds (VOCs), and bioaerosols.¹⁵⁹

In the feeding process, a low-crude protein feed is an economical and effective strategy to reduce odor emissions.¹⁹³ Lowering dietary protein in feed reduces N excretion, thereby decreasing total ammoniacal nitrogen in the excreta and ultimately mitigating ammonia emissions.

Livestock housing management systems are another major source of odor emissions. Key strategies to minimize odors include the separation and removal of feces and urine, using adsorbents or masking agents, and slurry acidification. In addition, improving the ventilation system by combining partial pit ventilation with normal ventilation can also effectively reduce odor emissions.¹⁹⁴

The manure management process emits significant gas pollutants. At this stage, semi-permeable membrane-covered composting (SMC), reactor composting, slurry cover, and slurry acidification are commonly used strategies to overcome these pollutants. SMC can effectively reduce odor emissions because odorants are inhibited by the covering material and absorbed by the water vapor layer.^{195,196} A floating plastic cover is another effective strategy for slurry storage, with an NH₃ reduction efficiency of 99.5%.¹⁹⁷

For end-of-pipe treatment, wet scrubbing and biofiltration are mainly used to remove gas pollutants. The main types of wet scrubbing are acid scrubbing, caustic scrubbing, and bioscrubbing. In these systems, gas pollutants

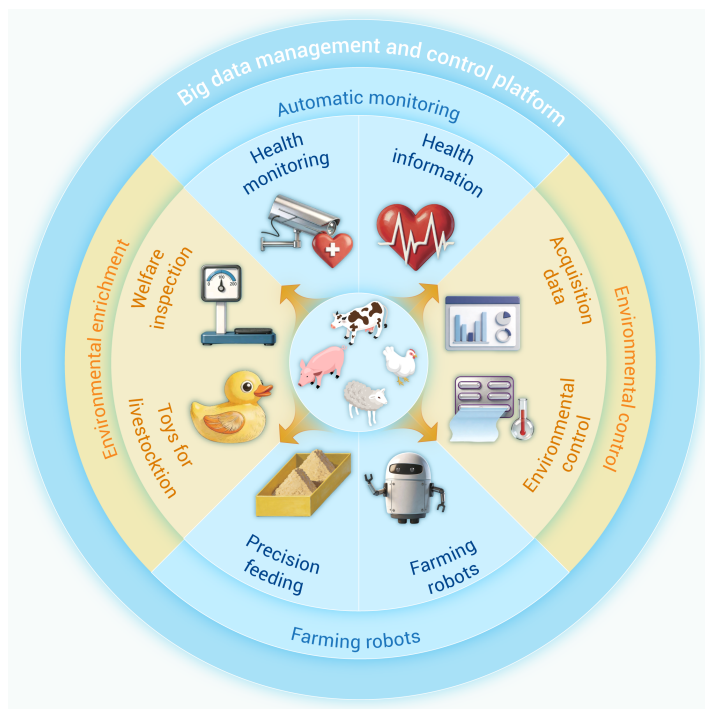


Figure 4. Smart farming technologies for livestock and poultry industry.

are absorbed, fixed, or degraded by washing solutions and filter bed materials.¹⁹⁸ The removal mechanism of biofiltration involves the degradation of organic substances into small molecular substances, such as carbon dioxide and water, by microorganisms.

WELFARE AND SMART FARMING TECHNOLOGIES

Intensive livestock production not only increases disease outbreak risks but also raises resource and labor costs, while putting pressure on the farm environments.¹⁹⁹ A crucial challenge for sustainable livestock production lies in maximizing feed efficiency while simultaneously reducing production costs and environmental impacts.²⁰⁰ Smart farming technology (Figure 4), driven by a new generation of information technology, enables the development of smart farming solutions for livestock and poultry production, including real-time data sensing, advanced data analysis and modeling, smart farming equipment automation, and big data platform-based control systems. These technologies are becoming the key tools for ensuring food security and environmental sustainability.

Effect of environmental enrichment on livestock production

In modern livestock production systems, animals require an enriched living environment to maintain their welfare and health. This enrichment allows animals to express their full range of natural and harmless behaviors. Environmental enrichment involves modifying the living environment of captive animals to facilitate the performance of natural, species-specific behaviors, and thereby improving their quality of life.^{201,202} These environments can be enriched by social, occupational, physical, sensory, and nutritional interventions.

Effect of environmental enrichment on animal behavior. Providing enough space for animals with toys in confined pens is commonly regarded as the enrichment measure for the farm animal environment. Animals in enriched environments exhibit aggressive and harmful behavior less frequently.²⁰³⁻²⁰⁵ For pigs, providing peat or straw in racks reduces inactive time and harmful social behaviors like aggressive while promoting exploratory behavior.²⁰⁶ Enrichment with toys can encourage playfulness and social interaction, increase foraging and exploring behavior, and reduce negative social behaviors, such as aggression, tail-baiting, and belly-nosing.^{205,207-210} The placement of toys plays a vital role in reducing aggressive behavior. Hanging the logs instead of lying on the floor results in less aggressive behavior.²⁰⁹ However, the size of enrichment objects should be

adjusted according to the age and body size of animals. For large animals tactile stimulation is also a commonly applied method to enrich their living environment,²¹¹ which can benefit not only young animals but also modify social behavior.²¹²

Impacts of environmental enrichment on animal production performance. Livestock production performance directly impacts farm profitability. Previous studies have shown that environmental enrichment increases animal growth rates^{205,207} and carcass weight.²⁰⁶ The backfat of pigs raised in the enriched environment is thicker than those in the barren environment, resulting in more tender pork.²⁰⁶ Providing toys during the procedures decreases stress and skin lesions.²¹³ For piglets, environmental enrichment during the suckling period has also shown a significant improvement in their average daily gain.²¹⁴ Except for a short-term improvement in the average daily growth of piglets, environmental enrichment also reduces the time it takes to reach the targeted market weight.²¹⁴ Regarding dairy cows, several studies have reported that enriching the milking environment by playing slow music can help them cope with stressors and improve milk yield by 3%, while fast music has a negative effect on milk yield.²¹⁵

Automatic monitoring technologies for livestock and poultry farming

Through monitoring and analyzing farming process information, health problems in livestock and poultry can be identified earlier, thereby improving the farming efficiency.

Automatic counting. Accurate counting of animals in the livestock farm is an essential aspect of precision farming. Advanced computer vision uses cameras and image analysis algorithms to detect and count animals. The camera can be set up at a specific location or in the way of the UAV.^{216,217} Image processing algorithms have been applied to automatic counting.²¹⁸⁻²²⁰ The counting method based on computer vision can be used in large open areas. Additionally, several other automatic counting methods are available, including radio-frequency identification tags, GPS collars, and Bluetooth low-energy tags.²²¹

Body size and weight measurements. Body size and weight are important metrics for tracking the growth and health of animals over time. Current research in smart livestock and poultry farming focuses on measuring these dimensions using 2D or 3D images. An image processing algorithm analyzes these images to estimate body size by extracting relevant features.²²² The 3D images can generate point clouds and improve estimation and measurement accuracy.²²³ Machine learning algorithms are used to construct animal weight estimation models.²²⁴ Body size and weight estimation based on machine learning vision are gradually replacing manual measurement. However, the accuracy and generalization capacity of the current estimation model still need improvement.

Sound monitoring. The sounds of livestock and poultry reflect their behavior and health status. Before analysis, pre-processing technologies, such as denoising, noise reduction, and sampling rate adjustment, are applied to the recorded audio. Consequently, feature extraction and machine learning algorithms are used to train the model for recognizing different types of farm animal sounds. Various sound classification models, such as the Transformer Convolutional Neural Networks (CNN), Deep Neural Networks-Hidden Markov Model (DNN-HMM), and support vector machine have been proposed.²²⁵⁻²²⁷ Several previous studies have employed these sound classification models to detect avian influenza-infected chickens, coughing pigs, and cattle in estrus through sound monitoring.²²⁸⁻²³⁰ However, automated recognition of livestock and poultry vocalizations faces challenges, such as removing noise from the farming environment and matching sounds to individual animals.

Activity and behavior monitoring. Animal behaviors are observable and measurable indicators of physiological status, well-being, and adaptation to environmental stimuli. Activity sensors and computer vision systems are widely used to monitor livestock and poultry movement and behavior. These devices track the position, speed, and time of movement, accurately locating individuals.²³¹ Computer vision-based monitoring systems are non-invasive and perform tasks such as detection, segmentation, tracking, action recognition and re-identification.²³² These technologies can also be integrated with deep learning algorithms to identify distinct behavior patterns.

Overall, technologies such as smart sensors, 3D cameras and infrared

thermography are now widely used in livestock and poultry farming. With the continuous improvement of various technologies and cost-effectiveness, the automatic acquisition of information related to livestock and poultry farming processes will become increasingly popular.

Environmental control technology and equipment for livestock and poultry houses

Environmental control is a crucial technology for maintaining the health of livestock and poultry, enhancing production efficiency, and regulating the environmental ecology. Adjusting micro-environmental indicators such as temperature, humidity, gas levels, dust, and lighting characteristics within livestock and poultry houses facilitates animal growth and reproduction.

Generally, wet curtain-fan cooling systems and hot air stoves are used to regulate the indoor temperature of housing facilities, thereby reducing the effects of cold or heat stress. The use of technologies such as spraying, dripping, floor cooling, and incubators can further control the local ambient temperature in the animal activity area, improving the thermal comfort for livestock and poultry while lowering cooling energy consumption. For example, floor cooling is highly effective in alleviating heat-stress in sows,^{233,234} while suckling piglets can act as biosensors for creep heating control by monitoring skin temperature, thereby reducing the electric energy consumption in recycled-packaging creepers.²³⁵ Ventilation and purification are the main contents of air quality control in livestock and poultry houses. A mixed ventilation system combines tunnel, natural, and tunnel/horizontal ventilation modes, adapting to seasonal differences while considering the temperature, harmful gas levels, and energy efficiency.²³⁶ Significant improvements in indoor air quality and reduction in emissions can be achieved with partial pit ventilation, which requires only 10% of the maximum ventilation, equipped with exhaust air cleaning in pig barns with ceiling ventilation systems, without affecting pig behavior.^{237,238} Air purification includes dust removal and deodorization.²³⁹ A three-stage biochemical waste gas treatment system has been developed, which involves absorbing particulate matter and some ammonia by spraying water, reducing ammonia emissions from manure by adding acids to lower the pH, and removing odors through microbial conversion. The removal rates of ammonia, TSP, PM10, and PM2.5 in this system reach 87%, 94%, 90%, and 97%, respectively, and the sobbing concentration is $\leq 300 \text{ OU/m}^3$. The intensity, wavelengths, duration, and rhythm of light have a significant influence on weight gain, feed consumption, age at first reproduction, egg production rate, and egg quality in livestock and poultry.^{240,241}

In the future, integrating artificial intelligence with traditional environmental control technologies will enable precise management of livestock environments. To achieve this, it is necessary to develop response models that link livestock and poultry behavior and physiology to environmental conditions, using multi-modal perception technologies like advanced sensors, machine vision, and voice recognition to collect real-time animal data.

Overall, the application of smart farming sensors into livestock production systems for continuously monitoring key welfare indicators, such as body temperature, activity levels, feeding behavior, and environmental parameters, offers new opportunities to enhance both animal welfare and food quality assurance. Those smart technologies enable individual animals to be monitored more closely, and in turn, provided tremendous data to get insights into animals' physiological and behavioral states, but also early detect the stress, disease, or suboptimal housing conditions, which allows for timely interventions, minimizing welfare compromise and reducing production losses.

Precision feeding technology and farming robots

Precision feeding technology aims to provide animals with an adequate amount of nutrients in a timely manner.²⁴² The key feature of this technology is the combination of dynamic nutritional models and smart feeding equipment, allowing the optimal allocation of feed resources and individual animal feeding.²⁴³

Precision feeding strategies are effective for adjusting the nutrient supply to individual animals at different times and reducing nutrient excretion.²⁴⁴ Improvements in nutrient use efficiency represent economic gains and the reduction of environmental footprint.²⁴⁵ There is a need to improve nutrient efficiency further and reduce the environmental impact of livestock production systems.²⁴⁶ Parameters that influence nutrient requirements include

environmental factors, animal health status, and behavior,²⁴⁷ and there is an urgent need to enrich nutritional modeling parameters.

The smart feeder focuses on the precision feeder and controller. The electronic feeding station for pregnant sows reduced nitrogen (18.5%) and phosphorus excretion (9%) and feed costs during pregnancy by €3.4.²⁴⁸ An increase in 1 kg/day feed intake can increase the farrowing rate of sows by 8% and reduce the interval between weaning and estrus by 1.8 days. The appetite of growing fattening pigs grows faster than their nutritional requirements, and the optimum concentration of nutrients in the diet decreases with age.²⁰⁰ For dairy cows, precision feeding equipment includes hanging rails, self-propelled, and conveyor belt systems.²⁴⁹ The cornell net carbohydrate and protein system has been redesigned and updated to improve its ability to develop and evaluate feeding programs for dairy herds with higher accuracy and efficiency.²⁵⁰ Precision poultry feeding technology enhances the industry's productivity and sustainability.²⁵¹

The growing interest in developing precision and smart farming has led to an increased use of robotics in agricultural production systems.²⁵² The most common challenge in robotics applications is the development of robots for specific agricultural tasks.²⁵² Robotization of farming processes is one of the global trends in the development of technological equipment for livestock farming.²⁵³ Automatic milking robots are among the earliest farming robots and have revolutionized dairy farming worldwide.²⁵⁴

Most farming robots specialize in areas such as perception and reasoning.²⁵² Farming robots employ intelligent path planning and adaptable navigation methods to support applications in various livestock farming environments. The study of path-planning algorithms is an important part of robot development, and the energy consumption of feeding robots is one of the crucial concerns in the path-planning process.²⁵⁵

Farming robots with simplistic operating interfaces reduce the complexity of farming processes, facilitating the spread of robots for livestock farming operations. A new research focus is to evaluate systematic approaches to automated task interactions to manage the entire poultry house efficiently.²⁵² Two-way communication between animals and machines is achieved by automatically conditioning animals to exhibit stimulus-controlled operant behavior.²⁵⁶ The use of farming robots is still in its early stages, and limitations such as accurately identifying abnormal individuals in group animal inspections and the realizing personalized and optimized designs still need to be solved.

The technology and platform of big data management and control for livestock and poultry farming

The technologies and platforms for big data control in livestock farming have emerged to manage and utilize data efficiently, thereby improving livestock farming efficiency.

The technology of big data storage for livestock and poultry farming.

The integration of livestock and poultry farming technology with big data is a significant driving force behind the refinement, automation, and intelligence of modern farming technology.

Cloud storage offers cost-effective and larger capacity compared to traditional warehouse storage. However, due to the inherent nature of cloud storage, security vulnerabilities such as data leakage cannot be fully addressed.²⁵⁷ In contrast, distributed storage based on blockchain technology has emerged, which works as a decentralized storage method. It improves fault tolerance and guarantees high performance and availability. For example, OriginTrail has used this technology to assign a unique identifier to each animal, providing a traceability solution for agricultural products.²⁵⁸ The key technologies of distributed storage have been used in HDFS, NoSQL, and NewSQL databases.²⁵⁹

Data privacy is crucial to the livestock and poultry farming industry.²⁵⁸ As data storage becomes more effective, big data technology can make a significant contribution to the livestock and poultry farming industry.

The technology of data analysis and mining for livestock and poultry farming. The data mining and analysis process involves interaction between a human and a computer based on the collected data from livestock and poultry farming.²⁶⁰ Via the priori constraints, the data are processed and analyzed to obtain information through cross-tabulation and regression analysis. On the other hand, data mining does not have to consider the data itself

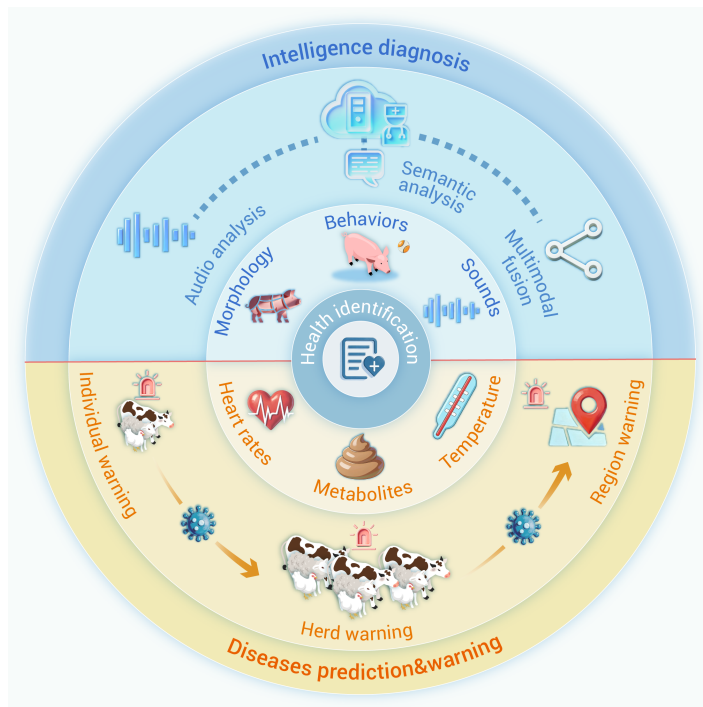


Figure 5. Overview of livestock and poultry disease intelligent diagnosis technologies.

but instead uses the information from the data analysis to reanalyze the value.²⁶¹ Data mining and analysis technology can be used to convert different types of farmed data into executable decisions through artificial intelligence algorithms, such as convolutional neural networks and recurrent neural networks.²⁶²

In the future, optimized deep learning algorithms for the deep mining and analysis of captured data will be a key point of research in big data technology for the livestock and poultry farming industry.

The visualization technology of big data for livestock and poultry farming. The visualization technology of big data provides livestock and poultry production managers with more detailed and intuitive data. With the help of various statistical charts, users can quickly understand the data and extract valuable insights.²⁶³

The visualization technology for big data is designed to utilize a model-driven approach, which can use the three-tier architecture system of Java 2 Platform Enterprise Edition. Many open-source frameworks are widely used in Europe. The effective construction of a visualization platform for livestock and poultry farming can significantly increase new employment and income opportunities for farmers, thereby improving production management efficiency. It is, however, less prevalent in small and medium-sized farms, which needs to be further promoted by technicians due to the application scale.

INTELLIGENT DIAGNOSIS FOR LIVESTOCK AND POULTRY DISEASES

The increasing ever-pressing animal diseases threatens to cross national and international boundaries, disrupt global trade, and pose severe risks to public health and food safety. In addition to relying on the traditional on-site veterinary diagnosis, advances in computer technology makes more timely, objective, and convenient methods for livestock and poultry disease management. These include abnormal health identification, early disease detection, and intelligent diagnosis. The related technologies are summarized in Figure 5.

Abnormal health identification

A number of automatic methods for identifying abnormal health conditions through digital and intelligent methods have been developed and applied to animals. These methods are commonly based on the digital characteristics of animal's appearance, behavior, sound, physiological parameters, etc.

Abnormal morphological identification. Morphological characteristics are

the most intuitive external manifestations of diseases in animals. Animals exhibit changes in their body structure, contour, and specific regions (such as the comb and legs) when sick. Nowadays, machine vision and infrared thermography have replaced manual labor and become the mainstream methods for obtaining animal images and identifying abnormal morphology without physical contact.

Machine vision technology monitors key morphological parameters of animals (e.g., body contour,²⁶⁴ bone structure,²⁶⁵ feather texture,²⁶⁶ etc.) to develop models based on principles of visible light and depth images. Models using machine learning and deep learning algorithms have achieved high accuracy (over 90%) in measuring phenotypic parameters²⁶⁷ and health evaluation.²⁶⁸

Infrared thermography technology is well-established for identifying morphological abnormalities in animals by detecting temperature differences between abnormal and normal tissue. It is particularly effective for ectoparasites²⁶⁹ and local tissue injuries,²⁷⁰ with an accuracy above 90%. For example, it enables the automatic counting of ticks, flies, and *Drosophila* on cattle²⁶⁹ and detecting diseased regions such as mastitis (accuracy of 83%),²⁷¹ dermatitis (above 81% accuracy),²⁷² and claw horn disruption lesions²⁷³ are well identified. Additionally, this technology can easily overcome background interference and accurately identify the comprehensive features of the animal's affected regions.

Abnormal behavior identification. There are several precision livestock farming (PLF) techniques for automatically and objectively capturing and identifying abnormal characteristics of farm animal behaviors, including camera systems, wearable sensors, and acoustic analysis.

As a non-invasive and cost-effective precision tool, camera systems have demonstrated great potential in recognizing the behavior of farm animals. A pose estimation-based model can accurately identify lameness in broilers with 90% accuracy by analyzing video footage.²⁷⁴ In recent years, depth cameras and infrared thermography cameras have been increasingly used. Based on depth images, identification models can automatically detect aggressive behaviors of group-housed pigs with an accuracy of 98%.²⁷⁵ Wearable sensors refer to small and lightweight sensors that can be attached to animals without interfering with their normal behaviors. Accelerometers and radio frequency identification (RFID) systems are two types of the most widely used wearable sensors for behavior monitoring, which could accurately simulate animal activity levels, postures, and behaviors, such as rumination of cattle (accuracy of 98%)²⁷⁶ and daily behaviors of pigs (accuracy of 98%)²⁷⁷ and poultry (accuracy of 89% in average).²⁷⁷ Applications of acoustic analysis in behavior recognition include monitoring poultry feeding behaviors by counting the number of pecks, as well as recognizing pig screams caused by tail-biting, ear-biting, and piglet crushes²⁵⁸ with accuracies above 89%. While most of them were only tested in labs, their performance may be reduced due to the noises from the production process.

Abnormal sound identification. Animal sounds provide valuable insights into their emotions and health conditions. Sound identification technologies automatically classify and recognize these sounds, distinguishing between normal and abnormal patterns to evaluate animals' health by analyzing differences in frequency, density, loudness, duration and other parameters.

To reduce stress on animals, researchers have developed both automatic sound recording devices and wearable sound acquisition devices to collect animal sounds data simultaneously. In terms of sound classification, algorithms based on CNN structures (such as CNN, DNN and Recurrent Neural Networks and their improved algorithms) have become the mainstream approach in recent years.²⁷⁸ At present, these technologies can identify and analyze various physiological sounds, including eating, drinking, biting, fighting, and singing, achieving an accuracy of around 80% in determining the foraging status of cattle²⁷⁹ and sheep.²⁸⁰ Additionally, these technologies can also detect pathological sounds such as coughing, sneezing, abnormal snoring, stress, and stress-related sounds, helping to facilitate early diagnosis of animal health or condition abnormalities. For example, the identification accuracy of chickens infected with avian influenza is more than 80%.²⁸¹

Body temperature monitoring. Animal body temperature is a key indicator of health and physiological state. For instance, estrus, pregnancy, lactation, stress, and disease may all cause elevated body temperature.²⁸² Compared to traditional rectal temperature measurements, real-time moni-

toring using implanted biosensors and infrared thermography has become increasingly popular in recent years as it reduces labor costs and minimizes stress.

Wearable temperature sensors have been miniaturized for easy attachment to animals, such as on the ears of pigs and cattle or under the wing of poultry. Researchers have used wearable wireless thermometers in poultry farms for early detection of avian influenza outbreaks.²⁸³ Alternatively, miniaturized microchips, encapsulated in biocompatible materials, can be implanted in the abdomen or under the skin.²⁸⁴ Examples of these commercialized technologies include DST nanoRF-T in Iceland, Anipill in France, and RFID LifeChip in the United States, with a high level of accuracy (0.1–0.2°C).

Unlike implantable and wearable sensors, which require restraint and handling of animals, infrared thermal technologies are non-invasive and stress-free.²⁸⁵ In pigs, the eyes and ear base are the optimal measurement sites, whereas in poultry, featherless areas like the head²⁸⁶ and face²⁸⁷ are typically used. Further details on infrared thermal technologies are described in the “Abnormal morphological identification techniques” section.

Physiological indexes identification techniques. Besides the abnormal indicators mentioned above, respiratory rate (RR), heart rate (HR), feces, and metabolites (e.g., VOCs) can also be used as indicators of the health status of livestock and poultry, which are commonly monitored using machine learning vision technology.

Studies on estimating RR using time-varying features extracted from pig abdominal movements have achieved correlation coefficients of 0.95 compared to manual measurement standards.²⁸⁸ Machine vision-based technology has successfully extracted the HR of pigs infected with *Actinobacillus pleuropneumoniae*, detecting HR changes 4–6 hours earlier than manual observation.²⁸⁹ Recently, photoplethysmography, an optical HR detection method, has gained attention for real-time dynamic monitoring due to its rapid,²⁹⁰ non-invasive capabilities. For the identification of abnormal feces, CNN-based models have been successfully used in a piglets²⁹¹ and broilers digestive system disease detector,²⁹² identifying five types of abnormal feces with an accuracy of 93.3%. Additionally, since VOC concentrations in poultry houses are associated with early-stages coccidiosis,²⁹³ sensor device can differentiate healthy birds from infected ones by detecting disease-specific VOC patterns.²⁹⁴

Diseases prediction

In recent years, the development of early warning, control, and monitoring systems for livestock and poultry diseases has advanced rapidly. These systems, supported by advancements in information technology, have strengthened disease prevention models and early warning capabilities.

Disease risk and warning models for animals. Once an animal in a herd is infected, close contact among herd members accelerates the transmission of the pathogen.²⁹⁵ Thus, early identification of infected individuals or herds is crucial for curbing outbreaks and reducing economic losses.

Unlike the sensing technologies and machine learning models for individual health monitoring (mentioned in the “Abnormal health identification” section), deterministic models analyze disease transmission mechanisms at the herd level. For example, differential equation models, such as the Susceptible Infected Recovered Model, have been used to study infections like foot-and-mouth disease virus²⁹⁶ and brucellosis.²⁹⁷ Due to the impact of precipitation amount, temperature, and other climatic factors on animal disease transmission, it is more suitable to use stochastic models to describe disease transmission, estimate the probability of eradication, and estimate the expected number of infected animals under different control measures.^{298–300} To our knowledge, animal diseases are closely related to the movements of animals and spatial heterogeneities. Additionally, seasonal brucellosis models incorporating nonlocal transmissions and spatial diffusion have been used to study how temporal heterogeneity and brucellosis affect outbreak severity.³⁰¹

Regional morbidity risk models. Regional morbidity risk models can help us to understand, measure, and analyze disease dynamics, as well as the natural and human environment factors associated with them in space and time. Supported by environmental data (especially remote sensing data), geographic information systems (GIS), and statistical models, these models can leverage limited epidemic distribution data from spatial points or regions to estimate and reduce disease risk in broader areas. Commonly used meth-

ods include general linear regression,³⁰² geographically weighted regression,³⁰³ the MAXENT model,³⁰⁴ the multilevel model approach,³⁰⁵ and Bayesian Disease Mapping,³⁰⁶ among others.

With the accumulation of disease and environmental data, the dimensionality of data has evolved from purely spatial to spatio-temporal, and statistical methods have advanced to accommodate this complexity. For example, the geographically weighted regression model has been expanded into a spatio-temporally weighted regression model³⁰⁷ by incorporating a time effect, allowing the assessment of the influence of each risk factor across time and space. Similarly, Bayesian spatio-temporal models have been developed to analyze spatio-temporal data more effectively.³⁰⁸ When spatial epidemic data exhibits a hierarchical structure, hierarchical Bayesian spatio-temporal models are often employed.³⁰⁹ With the development of AI, machine learning algorithms have begun to be applied to disease prediction, such as avian influenza.³¹⁰

Epidemic prevention and early warning systems for animals. Following recent global public health emergencies, the importance of animal disease surveillance as an early warning system remains a major concern.

Many countries have developed national epidemiological surveillance and reporting systems to assist nationwide disease control and prevention, as well as to detect emerging animal diseases. Examples of such systems include the Office International Epizooties-World Animal Health Information System (OIE-WAHIS),³¹¹ the National Animal Health Reporting System (NAHRS) in the United States,³¹¹ the National Animal Health Information System in Australia, the EpiMAN-FMD system in New Zealand, and the Animal Disease Information System in Europe. These systems rely on ongoing collaboration between governments, livestock and poultry industries, and animal health institutions. According to a NAHRS report (2017), Bovine Spongiform Encephalopathy-infected animals were detected with 95% accuracy, exceeding international standards.³¹² To improve global disease monitoring, strengthening partnerships and cooperation between national systems and WAHIS is essential to ensure two-way data exchange and information sharing.

Intelligent diagnosis

Intelligent diagnosis utilizes artificial intelligence (AI) technologies to identify diseases or assess the health status of livestock and poultry. At present, AI based disease diagnosis methods, including voice, semantic, and multimodal data recognition, as well as telemedicine and smart diagnosis systems, are well-developed and widely utilized.

Audio analysis techniques. Similar techniques and principles as described in the “Abnormal sound identification techniques” section. Farmers can quickly identify and prevent the transmission of animal sickness by monitoring sounds and conducting analysis. To date, studies have achieved a diagnosis of Newcastle disease, bronchitis, and avian influenza in -infected chickens with more than 90% accuracy.³¹³

Semantic analysis techniques. A semantic network is a framework for structuring human knowledge as interconnected nodes. With the development of AI, knowledge maps derived from semantic networks are now widely used since their proposal by Google.³¹⁴ In recent years, AI-driven knowledge maps have made significant achievements in the medical field, especially in providing an important means for remote diagnosis and treatment of diseases.

For human healthcare, comprehensive medical knowledge bases, such as Disease Ontology,³¹⁵ SIDER,³¹⁶ IASO,³¹⁶ Gene Ontology,³¹⁷ and UMLS,³¹⁸ have developed to facilitate intelligent diagnosis of diseases (e.g., liver disease,³¹⁹ lymphatic disease,³²⁰ breast cancer,³²¹ etc.). However, for livestock and poultry, semantic analysis remains underdeveloped. Existing veterinary databases focus mainly on swine³²² and bovine³²³ diseases, and the absence of standardized terminology hinders the application of international medical databases for veterinary disease research. This gap restricts progress in AI-based veterinary diagnosis via semantic analysis.

Multimodal data fusion techniques. As diverse smart techniques are developed and utilized in production, multimodal data has emerged as the major characteristic of the database in PLF. Multimodal data fusion aims to predict the results by integrating features from multiple modalities to utilize richer information and has found successful applications in various computer

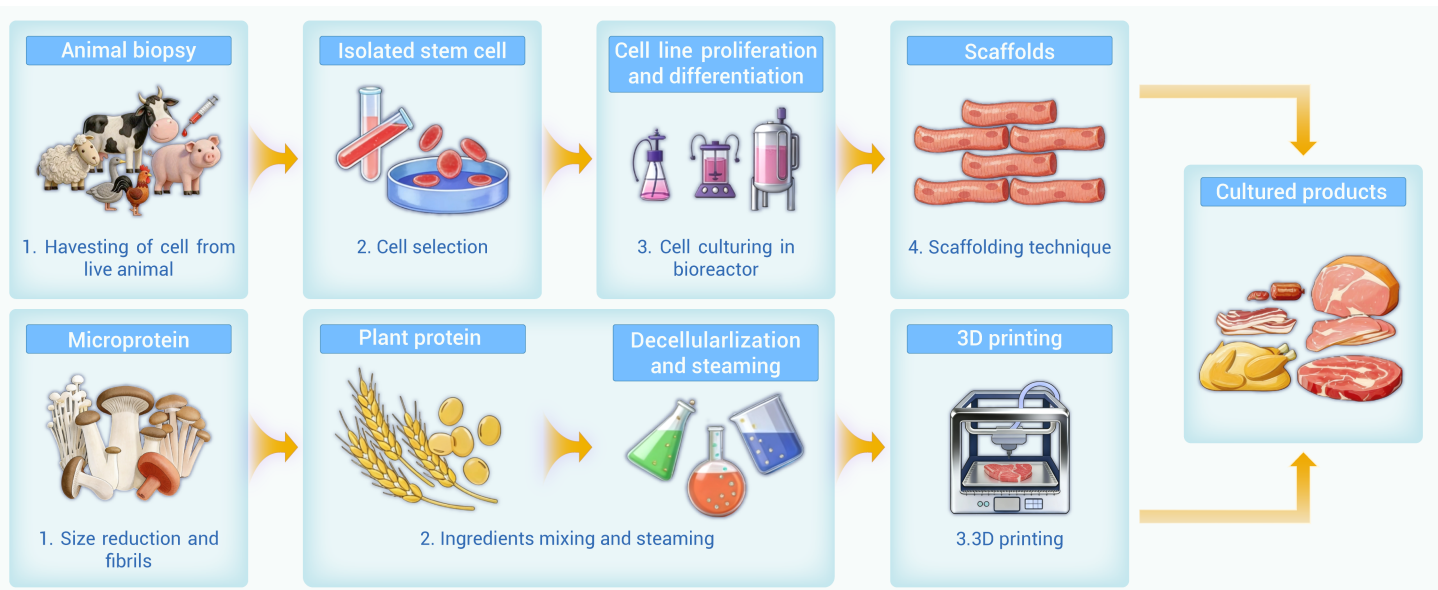


Figure 6. General schemes for production of artificial meat including cell-cultured meat, plant-based meat and fungi-based meat.

vision and biomedical tasks. However, limited research has been conducted to fuse features from multiple sensors for the intelligent diagnosis of livestock and poultry. Researchers have also been actively exploring the application of this technology in the livestock and poultry industries, highlighting its potential as an important direction for the future. Researchers developed a text-guided multimodal fusion network integrating text case reports and disease images to diagnose 6 classical swine diseases with the accuracy above 94%.³²² Recent advances in deep learning have developed a series of multimodal data fusion methods, making it feasible to apply multimodal data fusion in the intelligent diagnosis of animal diseases.

Telemedicine and smart diagnosis. Thanks to the development of PLF, disease diagnosis for farm animals has entered a new epoch, moving from the on-site mode, which is generally conducted in two ways: telemedicine and smart diagnosis.

Telemedicine systems allow veterinarians to remotely diagnose livestock and poultry using videos or audio recordings of sick animals. This approach enables each veterinarian to serve dozens of farms in a single day while mitigating disease transmission. Smart diagnosis, on the other hand, integrates AI, big data, decision-making, information and communication technology, and the Internet of Things. Automated collection of physiological, behavioral, and environmental data on farm feeds pre-trained models to generate predictions. The diagnosis results can then be provided after the analysis. In recent years, the introduction of Internet of Thing (IoT) and blockchain technology has further enhanced the transparency and credibility of the food safety traceability system. Integrating intelligent diagnosis results into the IOT and blockchain enables the recording of data throughout the entire supply chain from breeding to consumption, significantly improving the traceability of food safety.^{324,325}

In recent years, it has developed a series of systems and platforms for smart diagnosis, including web-based expert systems (smarter layer,³²⁶ dairy cow-vet³²⁷) and a computer-aided lung auscultation system.³²⁸ However, the lack of on-farm hardware requirements, limitations of local policies, and low acceptance of telemedicine among traditional farmers pose significant barriers to slow down its popularization.

FUTURE FOOD SUBSTITUTES FOR MEAT PRODUCTS

Global food security is a key issue in response to the call for reducing our carbon footprint, with a focus on efficient and healthy farming practices. In particular, citizens and consumers/consumer organizations pay special attention to animal ethics and animal welfare.³²⁹ Global meat demand is projected to rise by 70% by 2050. It will be a great challenge to realize such a big demand with a good animal welfare practice. Therefore, a more effective and secure substitute for animal meat is desperately needed to meet the

growing demand for meat protein without requiring drastic reductions in consumption or direct procurement from animal sources. Artificial meat, derived from various sources, including animal, plant, and microbial proteins, is a new target with a creative strategy that uses cellular engineering to meet global food demand. The production of these products involves cutting-edge technology and the integration of food safety standards that can safeguard public health by reducing contamination and ensuring traceability throughout the food supply chain.³³⁰ Here, the potential of cultured meat, plant-based protein, microbial protein, and the regulatory aspects of production and processing technology are summarized (Figure 6).

Cultured meat

Cultured meat production can reduce freshwater use by 96% and arable land use by 99%, reduce GHG emissions by 80%, and cut production time by 92% to produce the equivalent amount of protein compared to traditional meat production. Thus, it represents a sustainable protein source and has emerged as a new focus in cellular agriculture, recently attracting growing public interest.^{331,332} During cultivation, cells are supplied with nutrients and growth factors, proliferating and differentiating into the final product, which may or may not include a three-dimensional structure.³³³ The structure, texture, composition, appearance, flavor, and nutritional value of the final cultured meat product should be identical to real meat.

Seed cell acquisition and functional maintenance. Seed cells are crucial for the production of cultured meat. These cells for cultured meat should proliferate continuously *in vitro* while maintaining genomic stability to establish production cell lines. For large-scale production, the cells should be able to resist shear forces and efficiently differentiate into muscle, fat, or matrix-producing cells.

Several studies have focused on isolating high-quality muscle and fat stem cells by sorting or pre-plating techniques.³³⁴ To maintain the cell function of seed cells during long-term culture, many functional components, such as vitamin C and its derivatives, are necessary to promote cell proliferation and myogenic differentiation.³³⁵ In addition, smooth muscle cells³³⁶ and fibroblasts, which produce collagen and fat, are promising seed cells for cultured meat. For example, chicken fibroblasts suspended culture in a bioreactor for cultured fat production.

Large-scale cell culture. The establishment of a large-scale cell culture system based on bioreactors is crucial for scaling up cultured meat production. Suspension culture methods mainly include microcarrier-, immobilized-, aggregate-, and single-cell suspension systems.³³⁷⁻³³⁹ Both muscle and mesenchymal stem cells can be expanded in suspension using microcarriers. However, microcarrier-based culture is limited to cell densities of approximately 10^6 – 10^7 cells per mL, and the digestion and amplification process is

complex, hindering further scale-up of cultured meat production. Immortalized chicken fibroblasts cultured in serum-free, single-cell suspension can significantly improve the production efficiency.

Another vital aspect is bioreactor design. Cultivation in bioreactors involves complex interactions between gas, liquid, and solid phases. Therefore, scaling up bioreactor cultivation requires optimization of reaction kinetics, fluid mechanics, mass/heat transfer, biological characteristics, and automation. One study investigated the hydrodynamics and mass transfer characteristics of a spinner flask,³⁴⁰ then designed a 20 m³ stirred bioreactor model using computational fluid dynamics modeling, generating flow field data for industrial-scale translation.

Tissue and products formation. Cells are induced to differentiate into muscle fibers or fat, and adequately structured muscle tissues can be constructed with scaffolds. Bioactive compounds such as naringenin and ascorbic acid 2-phosphate enhance the formation and maturation of myotubes under both 2D and 3D culture conditions.³⁴¹ Similarly, lecithin activates peroxisome proliferator-activated receptor gamma (PPAR γ), inducing adipogenesis in immortalized fibroblasts.

In addition to cell differentiation, scaffolds are also essential for cultured meat production. Myotube formation and collagen production can be achieved on textured soybean scaffolds combined with various cell co-cultures.³⁴² Smooth muscle cells and mesenchymal stem cells with a strong ability to secrete extracellular matrix can attach well to peanut protein scaffolds and differentiate into cultured meat products with smooth muscle and fat properties. Differentiated cultured fat cells can also be blended with extruded soy protein, yielding cultured chicken strips with a similar aroma and flavor to conventional chicken.

For cultured meat production, food safety should be concerned in terms of the cell line itself (and its secreted substances), growth media and added compounds, scaffolds, and other materials used or manipulated during the process.^{343,344} Cultured meat requires specific regulatory approval before commercialization. In 2020, Singapore became the first country to approve the production and sales of cell-cultured chicken by Eat Just company. In 2023, the USDA and FDA approved regulatory clearance to Eat Just and Upside Foods companies for their cell-grown meat products. The FDA regulates the production process, including cell banks, cell development and differentiation, and cell collection, while USDA oversees the end products and labeling of cultured meat. This regulatory progress is expected to accelerate the industrialization of cell-cultured meat products globally, positioning it as a complementary approach to traditional livestock-based animal protein production. Given its sustainability benefits, cultured meat demonstrates significant market potential.

Plant-based meat

Protein sources. Soy protein is the most commonly used protein source in plant-based meat due to its nutritional value and better gelling properties (suitable for forming the anisotropic fibrous structure).³⁴⁵ Soy protein concentrate is rich in protein, polysaccharides, and other essential nutrients.³⁴⁶⁻³⁴⁹ Other proteins are often added to soy protein-based formulas to simulate the fibrous characteristics of meat. Wheat gluten (WG), for instance, is an excellent choice due to its strong viscoelasticity, elongation, and thermal coagulation properties.³⁵⁰ Additionally, WG compensates for soy protein's deficiency in sulfur-containing amino acids, which not only confers a complete nutritional profile on plant-based meat but also promotes the formation of a fibrous structure. For fibrous structure formation, plant protein must contain sufficient sulfur-containing amino acids. When the protein structure unfolds, exposed sulfhydryl groups form disulfide bonds, a critical step in creating meat-like textures.³⁵¹ The application of pea protein in plant-based meat has attracted increased attention due to the prevalence of soy protein allergies.³⁵² However, its gelling property is lower than that of soy protein, and its chemical structure is more prone to damage under extreme processing conditions.^{353,354} Therefore, strategies such as controlling extrusion parameters, adding other additional ingredients, or improving the gelling property of the pea protein are needed to achieve a satisfying fibrous structure. Beyond soy, wheat, and pea proteins, other plant proteins, such as peanut,³⁵⁵ rapeseed,³⁵⁶ mung bean,³⁵⁷ oat,³⁵⁸ fava bean,³⁵⁹ and hemp proteins, have also been used to develop plant-based meat products.³⁶⁰ Emerging protein sources,

fungal³⁶¹ and microalgae³⁶² proteins, are also being explored for their potential in next-generation meat alternatives.

Plant-based meat technologies. Plant proteins are different from animal proteins in terms of amino acid composition, intermolecular force, and spatial conformation, as well as it is difficult to directly simulate the structure of muscle fibers and bundles composed of actin and myosin. Thus, it is necessary to enhance the unfolding, rearranging, and cross-linking of natural spherical plant protein molecules through various food processing technologies, such as heating, shearing, or pressing, which are required to generate a fibrous structure similar to that of conventional meat. Food technologies, including extrusion, shearing, self-assembly, spinning (wet-spinning and electrospinning), 3D printing, and freeze-casting, have been extensively studied for producing protein fibrous structures. However, only the low-moisture extrusion technology (with a moisture content of 20%–40%) has been industrialized for producing meat alternatives, such as meatballs, hamburger cakes, and dumplings.³⁶³ High-moisture extrusion technology (moisture content of 40%–80%), which was developed in the late 1980s in France and Japan,³⁵⁹ showed the advantages of low-energy input (less than 1,000 kJ/kg), no waste discharge, high efficiency, and high fibrous structure quality.³⁶⁴ Thus, it is considered one of the best methods for developing plant-based, whole-cut meat substitutes.^{365,366} Recently, high-moisture extrusion technology has been applied to numerous meat alternatives using proteins from legumes, oilseeds, cereals, miscellaneous beans, and vegetables.³⁶⁷ The screw configuration in the extruder barrel and the cooling die design are the two key factors, and the protein fibrous structure is mainly formed at the connection of the extruder barrel to the cooling die through a "sub-layer transformation" cross-linking mechanism.³⁶⁴⁻³⁶⁷ Interestingly, mixed proteins from plants or microbes exhibit better textural and nutritional acceptability than single protein sources when used for extrusion.³⁶⁸

In addition to extrusion, 3D food printing has emerged as a promising technology for plant-based meat production.³⁶⁸ 3D printing, also known as fused deposition modeling technology, enables the construction of 3D geometric structures through layer-by-layer deposition using suitable materials (inks) based on digital 3D models, allowing for the customization of products.³⁶⁹ The main types of 3D printing include extrusion, inkjet printing, binder jetting, and bioprinting, with extrusion being the most common method for producing meat products.³⁷⁰ Compared to high-moisture extrusion, 3D printing features low energy input and operates without high pressure and temperature but depends on the high flowability of the printing material. The rheological properties should meet the requirements of extrusion and maintain the stability of the printed structure.³⁷¹ Plant proteins, such as soy protein, exhibit shear-thinning non-Newtonian properties that can reduce the extrusion pressure while maintaining flowability.

Sensory and nutritional aspects. Sensory properties are essential for consumer acceptance for plant-based meat. Simulating the fat fraction of meat is essential for replacing its juicy and textural properties.³⁷² Existing studies have focused on using plant-based high internal phase Pickering emulsions and gels to simulate animal fats.^{373,374} By cross-linking plant-based polysaccharides or proteins to form a network structure, properties such as rheology and texture are achieved similar to those of fats. Future research should also explore alternative components to replicate meat and fat flavors, thereby improving consumer acceptance.

Food safety issue. Although plant-based meat analogs have been considered prospective, allergens from food proteins and diverse ingredients are a major safety concern. Processing contaminants may occur in plant-based alternatives, along with anti-nutritional compounds, which interfere with the absorption of nutrients. Typical food safety hazards may also exist that are related to the plant, the product itself, or processing. To avoid or reduce such risks, measures should be taken during raw materials selection and processing.^{375,376}

Microbial protein manufacturing

Microbial protein meat, or single-cell protein, is from bacteria, fungi, algae, or agricultural waste materials. Compared to plants and animals, microbes grow significantly faster (with a doubling time of less than two hours compared to more than ten hours for plants and animals), thereby ensuring microbial protein production at a substantially higher temporal and spatial

efficiency. Filamentous fungi and mushrooms can naturally form filamentous mycelium, which can resemble a meat-like texture. Other microbes, including yeasts (i.e., *Yarrowia lipolytica*), are mainly used for protein production for ingredients in milk powder substitutes, cream, and pastes. The development of the above-mentioned products is straightforward. The first priority is to select a safe and optimal strain and then cultivate it (solid cultivation or submerged fermentation) to obtain the microbial cells. Finally, the cells are processed in a suitable manner to produce the final product. These products are commercially viable as food sources, and some microbial protein production is already available in the United States and European markets. However, the taste of such products is usually incomparable to real meat, as well as less acceptable and are mostly sold locally.³⁷⁷

SUMMARY AND OUTLOOK

The adoption of advanced technologies is essential in advancing ecological and healthy livestock and poultry breeding practices. These innovations reduce dependency on feed additives and antibiotics, improve food safety and quality, and ensure human health. Developing ecological and healthy breeding methods through harmless treatments can effectively reduce environmental pollution, promote harmonious co-existence between humans and nature, prevent environmental pollution, and improve the quality and safety of livestock products. By utilizing AI breeding technologies, the entire process of animal breeding can be intelligently managed, thereby enhancing production efficiency, reducing costs, and improving the quality of life for animals. Developing and cultivating alternative meat technologies not only meets people's demand for high-quality meat products but also minimizes the ecological environment and resource footprint. Collectively, by enhancing resource efficiency, reducing environmental footprints, and building more resilient production systems, the strategies outlined contribute to a more sustainable and secure global food system.

However, there are still many problems to overcome, but challenges and opportunities coexist. While the integrated industry chain promotes efficiency, it risks cross-segment gaps due to over-compartmentalization. For instance, advanced upstream technologies may neglect midstream welfare needs or downstream environmental costs, creating disconnects in sustainability goals. High-yield breeds could exacerbate waste management challenges, revealing systemic inefficiencies when segments operate in silos. Downstream innovations increasingly pressure upstream practices, but this reverse has limits. Market-driven demands for eco-friendly products often fail to address root causes, such as resource-intensive feed formulations or ethical farming trade-offs. Without upstream-midstream collaboration, downstream solutions remain reactive, not transformative.

It is precisely within this context that cross-disciplinary systemic integration becomes crucial for achieving the dual objectives of global food security and carbon neutrality. Such integration enables the transformation of isolated technological breakthroughs into holistic solutions. For food security, integration enhances the resilience of production systems and stabilizes food supply by minimizing losses across the supply chain through intelligent management and diversifying protein sources via alternative protein technologies. For carbon neutrality, it facilitates systematic accounting and reduction of the carbon footprint throughout the entire lifecycle—from feed production and farming practices to waste treatment. For instance, combining upstream breeding strategies, midstream farming practices, and downstream waste valorization technologies can achieve fundamental nutrient recycling and source-level reduction of greenhouse gas emissions.

Therefore, adopting an integrated strategy that reconciles operational efficiency with inter-sectoral equity emerges as a prerequisite for achieving substantive global food security. Future work should focus on the following aspects: (1) establishing a "big food view" to guide the transition of industrial farming towards nutritionally balanced, healthy, and environmentally sustainable practices, thereby reducing the environmental pressure on resources, ecosystems and greenhouse gas emissions; (2) promoting the innovation of livestock and poultry farming model and the upgrading of industrial farming towards eco-friendly practices, as well as explore the innovation of farming models, such as integrated crop-livestock systems, recycling agriculture, and welfare farming; (3) advancing intensive, mechanization, energy-efficient, and smart farming technologies for the modernized livestock and poultry produc-

tion, achieving high-quality outputs; (4) enhancing fundamental and applied research across all production stages, while improving early warning system to develop a series of healthy livestock and poultry farming technologies and standards. This method should pay attention to "safety and quality" while providing "environmental and economic" benefits, ultimately benefiting public health; (5) establishing biobanks for animal stem cells, optimized plant breeds, and selected microbial strains to enable high productivity and quality-assured production of cultured meat, plant-based meat, and microbial proteins.

To achieve a balance between human health and the ecological environment, we should integrate crop and livestock systems, establish modern intelligent farming systems, and deliver nutritious and healthy animal products alongside future food sources. By implementing the "big food view" and promoting global cooperation in resource sharing, we can realize true harmony between humanity and nature.

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AUTHOR CONTRIBUTIONS

F. L., Y. D., Y. F., Q. L., drafted the manuscript, M. W., H. D., L. Y., Y. Y., supervised the manuscript, and other authors critically revised the manuscript. All authors were responsible for the content of the manuscript and approved the final version for submission.

DECLARATION OF INTERESTS

Yulong Yin is an Editorial Board member of The Innovation Life and was blinded from reviewing or making final decisions on the manuscript. Peer review was handled independently of this member and their research group. The other authors declare no conflicts of interest.

DATA AND CODE AVAILABILITY

No new data were created or analyzed in this study.