

Review

Precision Feeding Systems in Animal Husbandry: Guiding Rabbit Farming from Concept to Implementation

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Abstract

Precision Feeding Systems (PFS) demonstrate transformative potential in advancing sustainable and efficient production within modern animal husbandry. However, existing research lacks a synthesis of PFS applications in livestock farming and offers little targeted guidance for China's rapidly growing rabbit industry. The objective of this review is to bridge this gap by synthesizing current knowledge on PFS technologies—including sensor networks, artificial intelligence (AI), automated controls, and data analytics—and providing a structured framework for their implementation in rabbit production. This study selects and analyzes 112 core references, establishing a foundational database for comprehensive evaluation. The key contributions of this work are threefold: first, it outlines the core components and operational mechanisms of PFS; second, it identifies major challenges such as sensor reliability in dynamic environments, data security risks, limited explainability of AI models, and interoperability barriers; and third, it proposes a customized strategy for PFS adoption in rabbit farming, emphasizing phased implementation, cross-system integration, and iterative optimization. The primary outcomes and advantages of adopting such a system include significant improvements in feed efficiency, resource utilization, animal welfare, and waste reduction—critical factors given rabbits' sensitive digestive systems and precise nutritional needs. Furthermore, this review outlines a future research agenda aimed at developing resilient sensors, explainable AI frameworks, and multi-objective optimization engines to enhance the commercial scalability and sustainability of PFS in rabbit husbandry and beyond.

Keywords: precision livestock farming; precision feeding; rabbit farming; robotic systems; artificial intelligence



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1. Introduction

As a cornerstone of global food security, livestock production plays a pivotal role in sustaining the supply of meat, dairy, and egg products. However, contemporary animal husbandry confronts multifaceted challenges arising from evolving consumer demands and intensifying environmental constraints [1]. Modern markets now require not only quantitative sufficiency but also enhanced product quality, safety assurance, and diversified offerings—a paradigm shift demanding fundamental transformations in production architecture, quality control systems, and value-chain optimization [2,3]. Evidence indicates that traditional extensive farming practices not only fail to meet the aforementioned

market demands, but also increasingly prove inadequate in addressing critical issues such as low resource utilization efficiency, failure to improve production efficiency, and compromised animal welfare standards. This operational crisis has accelerated the imperative transition toward precision livestock farming (PLF) systems [4]. Through precision nutrition management, predictive disease surveillance, and microenvironmental modulation, these intelligent systems demonstrate remarkable potential in optimizing production efficiency (15–22% yield improvement reported in dairy operations [5,6]), reducing feed conversion ratios (FCR reduction up to 18% [7]), and minimizing environmental footprints (28–35% reduction in nitrogen emissions [8,9]). Of particular significance in PLF implementation is precision feeding technology—the operational nexus integrating nutritional science, mechatronics, and predictive analytics. Leveraging cutting-edge technologies encompassing information technology, sensor technology, artificial intelligence technology and automation control technology, precision feeding technology enables real-time monitoring and data-driven decision-making across production cycles [10,11]. By dynamically adjusting feed composition, delivery timing, and portion sizes according to real-time physiological parameters and growth stages, this approach achieves dual objectives of minimizing feed waste (reported 12–25% cost reduction) while maximizing nutrient utilization efficiency [12]. Rabbits have special requirements for precision feeding due to their unique physiological vulnerability (requiring regular feeding times and quantities), nutritional sensitivity (requiring precise energy-protein coupling), and digestive system characteristics (requiring dynamic intake according to physiological stage needs) [13,14]. However, the current disparity in rabbit farming scale has led to inconsistent farming environments and standards, resulting in slow development of intelligent technology in rabbit farming. This makes it difficult to meet the strict requirements for precision feeding posed by rabbits, which have relatively small feed intake.

Over the past decade, the precision livestock farming (PLF) domain has amassed over 68 review publications [15], demonstrating multidimensional research expansion: Technologically, studies encompass animal welfare monitoring (e.g., stereotypy recognition, thermal stress responses) [16–19], health diagnostics (mortality detection, disease alerts, lameness identification) [20–23], group management (auto-sorting, estrus detection) [24–28], and system implementation (IoT architectures, edge computing deployment) [29–32]; Application-wise, established frameworks evaluate dominant species (swine, cattle, poultry) [33–35], providing adaptation paradigms for minor species. However, existing reviews exhibit critical structural limitations. Firstly, the absence of cross-species evaluation frameworks for universal production stages (e.g., environmental control, feeding management) impedes knowledge transfer from extensively studied species (swine/poultry) to neglected species (rabbits/sheep). Secondly, research gaps in rabbit applications persist. Despite rabbit farming being the fastest-growing specialty sector due to unique biological traits (hindgut-fermenting digestive physiology, 42-day hyper-compressed reproductive cycles) and dual-output markets (meat/pelt) [36,37], there was only one review related to rabbits, and only one publication was identified through a detailed search using the keywords ‘rabbits and breeding.’ These dual deficiencies leave developers of rabbit precision feeding systems without theoretical guidance, necessitating urgent establishment of production-phase-oriented cross-species analytical matrices and full supply chain technological roadmaps [38–41].

In view of this, this study aims to bridge these research gaps by conducting a literature review of precision feeding systems, with a specific focus on guiding their application in rabbit farming. Our analysis, built upon a foundational database of 112 core publications, thoroughly evaluates PFS technologies and their applications across livestock species. Key findings from this synthesis reveal a significant disparity in technological adoption, with

well-established systems in swine and poultry yet minimal application in rabbit production, despite its unique needs and growing industry importance. The analysis further identifies critical cross-species transferable technologies and species-specific adaptation requirements. Consequently, this review provides a comprehensive implementation framework for PFS in rabbit farming. It offers targeted guidance on technology selection, equipment configuration, system integration, and adaptive management strategies. By translating technological insights from other species and addressing rabbit-specific challenges, this work provides much-needed theoretical guidance and practical references for farmers, thereby facilitating the wider application and development of precision livestock farming in the rabbit industry.

2. Precision Feeding Under Precision Livestock Farming

In the early stages of livestock farming, operations were typically small-scale, with farmers allowing animals to grow naturally. This approach involved providing ample feed and permitting animals to eat freely according to their appetite, known as *ad libitum* feeding [42]. This method was straightforward, requiring no complex feeding plans or precise control, ensuring that animals did not suffer from growth issues due to insufficient intake, which was particularly beneficial for the rapid growth of young animals. Additionally, limited labor resources in early farming made *ad libitum* feeding advantageous, as it reduced the need for frequent feeding interventions. However, as farming scales expanded and demands for improved productivity and animal quality increased, the drawbacks of *ad libitum* feeding became apparent. Issues such as significant feed waste and health problems like obesity in some animals due to overconsumption emerged, negatively impacting reproductive performance and product quality [43,44].

In response, the advantages of restricted feeding began to gain attention. Restricted feeding involves farmers developing detailed feeding plans based on factors such as animal breed, age, weight, and production purpose, strictly controlling feed amounts and feeding times [13]. This method allows for precise control over the nutritional intake of animals, significantly improving feed utilization, minimizing unnecessary feed waste, and reducing farming costs [45]. For breeding animals, restricted feeding effectively manages weight and body condition, maintaining them in optimal reproductive states to ensure reproductive performance [46]. Moreover, effective control of animal intake reduces wear and tear on facilities like feeders and waterers, extending their lifespan and further enhancing overall farming efficiency.

Building upon restricted feeding, there is now a pursuit of more refined and scientific feeding methods, known as precision feeding [47]. Precision feeding utilizes various sensors and electronic identification technologies to monitor key information about individual animals in real-time, such as weight changes, health status, and feeding habits [48]. Based on this data, specialized formulation software prepares feed that matches the animal's current nutritional needs, which is then delivered through intelligent feeding equipment at precise times and quantities [49]. This approach not only retains the benefits of restricted feeding (enhanced feed efficiency and controlled animal condition) but also enables personalized feeding plans. These plans better align with individual animals' needs across growth stages and physiological states. Additionally, precision feeding promotes healthy growth, optimizes production performance, and significantly improves the yield and quality of agricultural products such as meat, milk, and eggs [50]. Environmentally, precision feeding plays a positive role by reducing pollution issues arising from feed waste, advancing livestock farming toward efficiency, quality, and sustainability. The stages of development of feeding practices are shown in Figure 1.

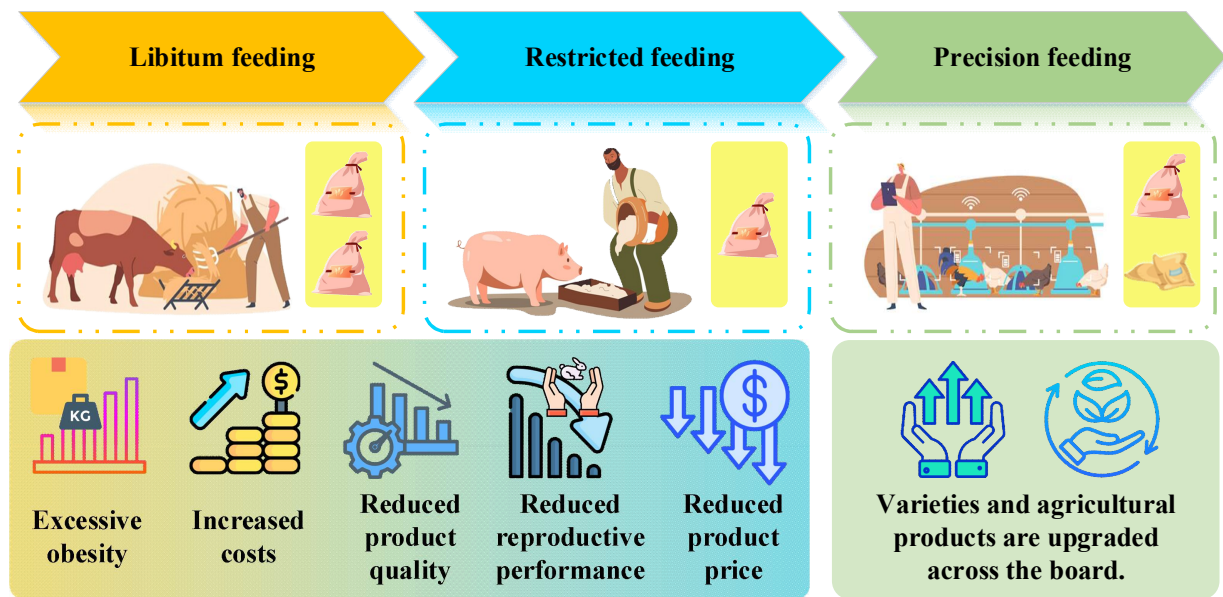


Figure 1. Stages in the development of feeding practices.

3. Research Methodology

This study strictly followed four phases: problem formulation, literature review, quality assessment, and data synthesis [51,52]. Data sources encompass academic journal articles, industry research reports, technical white papers from agricultural equipment manufacturers, and empirical data from large-scale livestock farms. The databases we selected include Web of Science, Science Direct, IEEE, Scopus, etc. Core search terms were combined using Boolean logic operators: (“different species names” AND “precision livestock farming” OR “precision feeding systems” OR “feeding robots” OR “animal production” OR “feeding behavior”). The publication timeframe was delimited to 2010–2024 to ensure contemporaneity. These publications were classified into three analytical dimensions: (1) by technological core (sensor networks, data analytics, AI algorithms, actuator systems), (2) by application species (swine, cattle, poultry, and rabbits) and (3) by implementation challenges (reliability, interoperability, scalability).

The literature screening implemented a three-tiered evaluation mechanism:

Reason 1 (Thematic Relevance): Research objectives must demonstrate explicit focus on Precision Feeding System (PFS) technologies;

Reason 2 (Methodological Rigor): Studies must feature reproducible experimental designs with quantitative validation;

Reason 3 (Practical Applicability): Research should substantiate real-world scalability potential.

Ultimately, 230 of the initial 342 studies were excluded, leaving 112 studies meeting the aforementioned quality standards to form the theoretical foundation. This included 75 academic studies and 37 commercial products. Details of the literature screening process are presented in the PRISMA flow diagram (Figure 2).

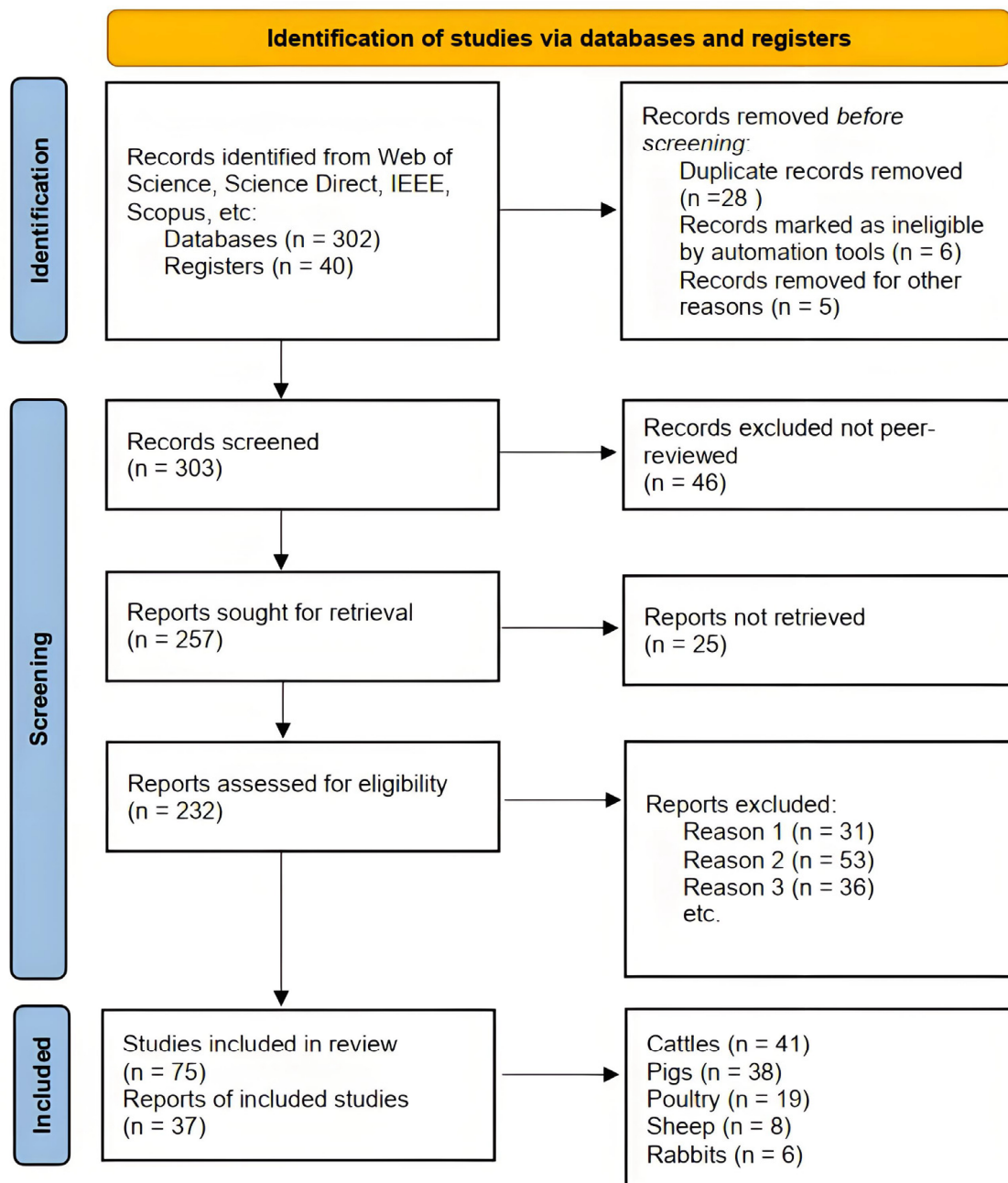


Figure 2. PRISMA flow diagram for the review.

4. General Technologies in Precision Feeding Systems

The development of precision feeding systems involves the integration of various technologies, including sensor technology, information technology, artificial intelligence, and automation control. Sensor technology serves as the data source, collecting raw data; information technology handles the transmission, storage, and integration of this data; artificial intelligence analyzes and makes decisions based on the data; and automation control executes the corresponding decisions to perform actual feeding operations. These four technologies each play a unique role while collaborating to form the technical support system for precision feeding. An overview of the general technology of the precision feeding system is shown in Figure 3.

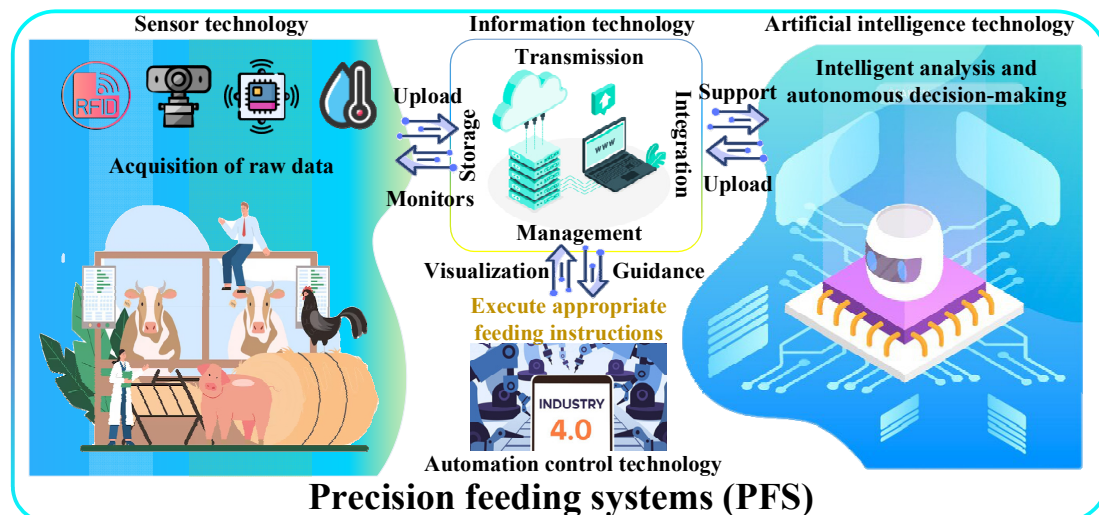


Figure 3. Generalized technological interrelationships of precision feeding systems.

4.1. Sensor Technology

The precision feeding system primarily relies on sensor technology to guide the feeding process. The sensors used can be categorized into two types: one focuses on abiotic factors such as feed, feed troughs, and farming environment facilities, while the other targets the animals themselves [53]. Sensor technology enables the collection of extensive data from multiple sources [54], including basic information about individual animals (such as breed, age, gender), feeding data (such as feed intake, feeding time, feeding frequency), health data (such as disease records, health check indicators), feed-related data (such as nutritional composition, raw material sources, and quality variations across batches), and environmental data (such as temperature, humidity, and air quality) [55–57].

4.1.1. Sensor Technology for Non-Living Things

Sensor technology focused on physical properties of objects is relatively common in the early stages of animal farming, primarily used to monitor abiotic factors. Commonly used devices include weight sensors and flow sensors, which are typically installed at feed intake points, such as the feed trough, and operate based on principles like weighing, electromagnetic induction, and turbine rotation to measure the feed flow [58–60]. For instance, when feed is transported from a storage silo to the feed trough through a pipeline, an electromagnetic flow sensor calculates the feed flow by detecting the electromagnetic changes caused by the feed cutting through the magnetic field lines [61]. This allows the system to track the amount of feed dispensed per feeding session and the flow rate over time. Once the feed reaches the trough or storage container, weight sensors are often installed at the bottom of the trough or beneath the storage container to detect pressure changes caused by the feed's weight, enabling real-time monitoring of remaining feed levels [62]. This data helps farmers accurately assess animals' feeding behavior, such as intake speed and quantity, allowing for adjustments in feeding strategy as needed. Mosquera et al. presented a mechatronic system to automate the dosing of cattle feed. The weighing specifications are divided into 3 types, which are dispensed using the force exerted by the transducer and the rotating arm [63]. Bloch et al. developed a weighing system including the suspension of a single load cell to provide feed mass measurements [64]. In modern pig farms, weight sensors typically transmit data on remaining feed every set interval (e.g., every half hour) to the control system, providing farmers with insight into feed consumption rates and the feeding patterns of the herd at different times. Additionally, photoelectric or ultrasonic level sensors can also be used to monitor feed levels. In poultry farms, when the feed level

in the trough is low, the level sensor sends a signal to the control system to prompt the addition of feed [65].

While the studies mentioned above focus on monitoring the physical properties of abiotic factors, there is also research on component analysis sensors that directly detect the feed's composition using techniques like near-infrared spectroscopy and electrochemical analysis [66,67]. Near-infrared spectroscopy sensors emit specific wavelengths of near-infrared light onto the feed and analyze the absorption and reflection characteristics of the feed's various components to determine the content of nutrients such as proteins, fats, carbohydrates, vitamins, and minerals [68,69]. Electrochemical analysis sensors, on the other hand, detect the concentration of specific feed components by measuring the electrical signal changes generated by chemical reactions. In feed production facilities or farms, component analysis sensors can be used in quality control processes to ensure that newly mixed feed meets the preset nutritional standards [70].

Although environmental sensor technology primarily monitors parameters like temperature, humidity, and air quality, these environmental factors can indirectly affect animal feeding behavior and nutritional needs. Studies have shown that feed intake may decrease in high-temperature environments, requiring adjustments in feeding time and amount [71]. Therefore, environmental sensors play a crucial role in ensuring the rationality of the feeding process in precision feeding systems. Figure 4 shows the application of sensor technology for non-living things (using cattle as an example).

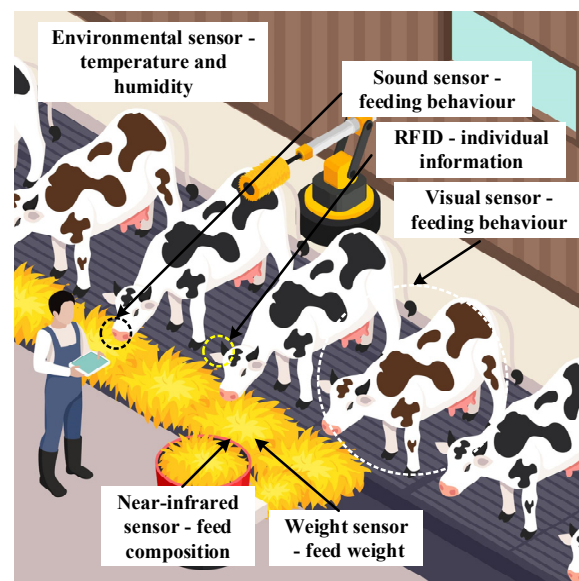


Figure 4. Sensor technology application (using cattle as an example).

Based on the above analysis, the current value of abiotic sensing systems lies in establishing a data-driven, objective perception layer that replaces empirical judgment. This provides a robust foundation for feed management, environmental control, and understanding interactions among abiotic factors—such as how environmental stress influences physical feed intake. Its primary advantage resides in enabling efficient, automated monitoring of abiotic conditions at the group level. However, this system exhibits inherent limitations: physical sensors and composition analyzers provide static or herd-averaged feed property data, while environmental sensors capture macro-scale barn conditions. Collectively, these technologies cannot directly perceive or respond to individual animals' physiological states or differentiated needs—creating a disconnection between monitored objects (abiotic elements) and acting agents (biological entities). This necessitates complementary biosensing technologies. Future development of abiotic sensing should focus on:

(1) Enhanced Integration and Environmental Robustness: Developing multi-parameter sensor nodes (e.g., combining physical measurements, key constituents, and environmental parameters) with tolerance to dust, humidity, corrosion, and mechanical stresses in farm environments to reduce maintenance costs; (2) Interfacing with Biosensing: Recognizing the boundaries of abiotic data and proactively designing data fusion frameworks with emerging individual behavior recognition (e.g., computer vision) or physiological monitoring technologies. This creates compatibility for future closed-loop, animal-state-aware feeding systems.

4.1.2. Sensor Technology for Livestock and Poultry

As livestock farmers gain a deeper understanding of the individual states of their animals, there is an increasing demand for more refined management strategies. In the past, farmers made rough assessments of animal health by manually observing behaviors such as feeding patterns and activity levels. However, with the advancement of interdisciplinary fields such as electronics, communications, and biomedicine, technologies like Radio Frequency Identification (RFID) sensors for precise animal identification, along with bioelectrical sensors and visual sensors for monitoring animal health and behavior, have emerged [72,73]. These developments aim to leverage technological tools to gain insights into the complex physiological and behavioral traits of animals, enabling more accurate health management and personalized feeding strategies.

Common technologies include RFID ear tags and electronic collars, which can precisely identify individual animals, record their identity information, and associate it with corresponding data such as feeding history, health status, and growth data [74,75]. This allows for targeted feeding at the individual level. In dairy farming, for example, each cow wears an RFID ear tag, enabling the system to quickly identify the cow upon entering the feeding area and dispense feed according to its specific needs. Chang et al. used a microphone to capture sounds from cows' throats to measure ruminations and feed intake [76]. Muir et al. developed an automated feeding system capable of detecting and recording unique electronic RFIDs associated with unique feed events and accurately capturing the weight of feed removed [77]. Over time, accumulated data with individual identification, including feeding and health records, facilitates in-depth data mining and analysis. By analyzing the feeding data from pigs at different growth stages, alongside their final weight and meat quality, more optimal feeding strategies can be derived. Additionally, this data analysis can reveal correlations between potential health issues and feeding behaviors, providing scientific evidence for more informed management decisions [78].

Research on bioelectrical sensors is relatively limited, but these sensors work by detecting changes in the bioelectrical signals within livestock via electrodes in contact with their body surfaces [79]. For instance, electrocardiogram (ECG) signals can be used to assess the cardiac function and heart rate of livestock, while electromyogram (EMG) signals reflect the activity and fatigue levels of muscles [80]. Since the feeding process is often accompanied by muscle activity, EMG signals can be used to analyze feeding strength, frequency, and other behavioral characteristics [81]. By comparing the EMG signals from normal feeding versus abnormal feeding (such as when oral pain or digestive issues lead to irregular feeding), farmers can more accurately assess whether the feeding behavior is normal and adjust feeding strategies accordingly, such as switching feed types or examining oral health, ensuring normal feeding patterns.

Visual sensors, typically consisting of cameras and image recognition algorithms, are installed at key locations within animal housing, such as above feeding or activity areas, to capture real-time images of livestock appearance and behavior [82]. Advanced image recognition technology is then employed to analyze the animals' body shape, posture,

behavior, and mental state. Regular monitoring of body shape and posture, combined with temporal data, enables accurate assessment of growth rates and health conditions [83]. For individuals with slow growth, targeted checks on nutritional intake and the presence of potential diseases can be conducted [84]. Feeding strategies can then be adjusted, such as increasing nutritional content or altering feeding frequencies, to help the animal catch up with the growth pace of the group, ensuring uniform growth. Yang et al. developed a real-time detection model for individual yak feeding behavior using the YOLO family of models and the StrongSORT tracking model, an approach that holds promise for long-term yak feeding monitoring [85,86]. Figure 4 shows the application of sensor technology for livestock and poultry (using cattle as an example).

Based on the comprehensive analysis, sensor technologies targeting livestock and poultry organisms constitute the core driver of precision feeding systems by establishing a closed-loop “identity recognition–physiological feedback–behavioral analysis” chain. Vision-AI systems dominate precision feeding research through their non-contact, full-dimensional monitoring capabilities, utilizing deep learning to parse real-time video streams for concurrent tracking of individual body condition development, feeding behaviors (e.g., feeder occupancy duration, swallowing frequency), and group interactions (e.g., competition intensity, avoidance behaviors), thereby constructing dynamic nutritional requirement models. While RFID technology serves as the foundational identity anchor enabling individual identification for visual data streams and facilitating individualized feed delivery by smart feeders based on historical performance data, its limited functionality is progressively integrating into vision systems as an auxiliary module. Biosensing technologies such as electromyography (EMG) demonstrate precise oral pathology diagnosis via masticatory muscle signals in laboratory settings, yet their commercial adoption remains restricted due to low animal tolerance for contact electrodes and unstable field signals, primarily serving as supplementary validation for visual swallowing recognition. Current vision technologies face critical scenario adaptation bottlenecks: individual occlusion in intensive group housing causes missed detection of key behaviors (e.g., swallowing), compromising feeding efficacy assessment; low-light/high-dust environments degrade body condition scoring accuracy, hindering nutritional optimization; and superficial behavioral analysis fails to quantify deep stress indicators like feeding urgency levels. Future breakthroughs require a tripartite advancement strategy: establishing a holistic perception fusion hub using spatiotemporal alignment algorithms to generate “individual–environment–feed” interaction atlases; enhancing environmental robustness through multispectral imaging while extracting refined body condition features via 3D pose estimation; and developing behavior–physiology correlation models to decode stress mechanisms.

4.2. Information Technology

Information technology is in the middle stage of the precision feeding system, integrating multiple roles such as data management, big data analysis, system synergy and remote monitoring [87–89]. As the foundation for data collection, integration, and storage, it provides a comprehensive database for feeding operations.

In large-scale livestock farming, the volume of data generated by precision feeding systems is immense, and local servers often struggle to meet the demands for storage and rapid computational processing. Cloud computing technology offers powerful cloud storage services, allowing farming enterprises to upload vast amounts of feeding-related data to the cloud, ensuring both data security and scalability [90,91]. Additionally, cloud computing platforms provide robust computational capabilities, enabling fast processing of complex data tasks.

Big data analytics technology consolidates disparate and complex data obtained from multiple sensors into a unified data platform. By establishing relational databases or data warehouses, data in different formats and from different sources can be standardized for effective system access and analysis. Data mining algorithms and statistical analysis methods are employed for in-depth analysis of the integrated data [92]. For instance, by analyzing feeding patterns across various growth stages and animal breeds, trends in feed intake changes during different seasons and health conditions, as well as correlations with nutritional components of the feed, can be identified [93].

Internet of Things (IoT) technology connects the numerous hardware devices within a precision feeding system into an integrated network, enabling seamless communication. Individual monitoring devices, such as RFID sensors and bioelectric sensors installed on animals, are linked with weight sensors, flow sensors in feed troughs, and environmental sensors for temperature and humidity, all communicating via network protocols (e.g., Wi-Fi, Bluetooth, ZigBee) [94,95]. This interconnectivity allows real-time information exchange between devices. Through IoT technology, producers can remotely monitor the operational status of various devices within the precision feeding system via terminal equipment, such as ensuring that automated feeding devices are functioning correctly or that sensor data is transmitted accurately [96]. In the event of an anomaly, the system promptly sends alerts, enabling producers to respond quickly and resolve issues. Chen et al. combined a rule-based expert system and the Internet of Things (IoTs) to develop a precision feeding system that can accurately meet the nutritional needs of sows during gestation and lactation stages [49]. Chiu et al. used an Artificial Intelligence of Things (AIoT) precision feeding management system to improve existing feeders [97]. Furthermore, IoT technology facilitates the automation of the feeding process, automatically triggering appropriate feeding actions and adjusting feed quantities based on preset feeding rules and real-time data, thus achieving an unattended. Mobile applications and farm management tools are designed to enable livestock farmers to view relevant details about the farming process via their mobile phones or a central platform, and even remotely control the operating status of related equipment. The advantage is that the farming process can be viewed and managed anytime, anywhere, but the disadvantage is that it requires strong network transmission capabilities to ensure rapid signal response. Figure 5 shows the application of Information technology for cattle.

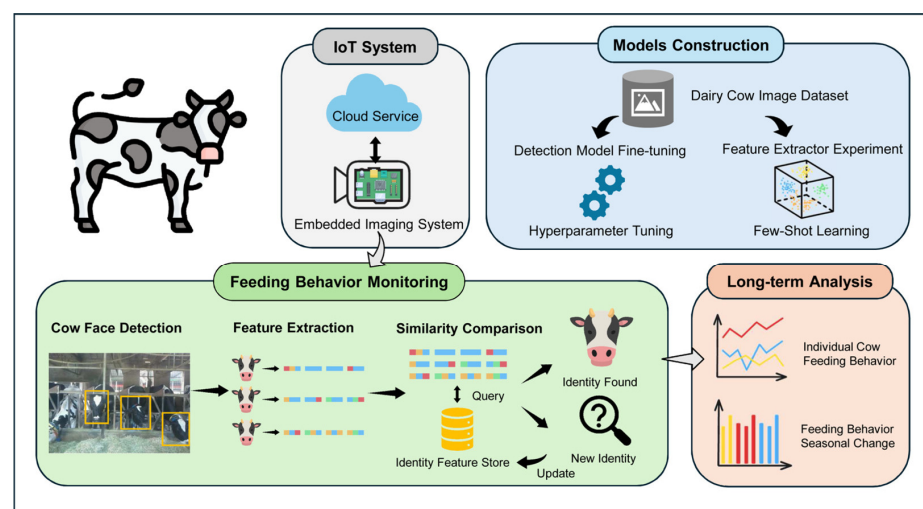


Figure 5. Information technology application (using cattle as an example [98]).

Precision feeding systems face a fundamental data abundance vs. decision timeliness paradox. IoT expansion enables multidimensional data collection spanning individuals to

groups and feed to environment. Cloud computing reveals critical patterns like models linking environment to feed intake or disease-precursor feeding fluctuations. However, centralized processing creates multi-layered delays: Network latency causes stress responses to lag physiological changes; computational bottlenecks miss biological windows (e.g., untimely sow lactation adjustments); protocol heterogeneity increases integration costs. More critically, computation-intensive models (e.g., multi-objective optimization for 10,000-head farms) exclude small-to-medium farms from technological benefits. This creates big data-driven feeding inequity. Technological solutions must prioritize four areas: edge computing deployment, standardized Agri-IoT protocols with unified interfaces, cloud-edge collaboration (real-time tasks at edge, long-term optimization in cloud), and progressive model compression like distilling LSTM into micro knowledge graphs. The ultimate goal is maximizing feed conversion efficiency under hardware constraints by reducing inefficiencies in data-decision-execution chains.

4.3. Artificial Intelligence Technology

Artificial intelligence (AI) technology was not a mandatory component in the early development of precision feeding systems, which initially relied on basic sensors, simple automation controls, and human experience to achieve a certain degree of feeding accuracy. However, with the advancement of smart livestock farming, the demand for precision feeding has increased significantly. Producers now seek deeper insights into animal feeding behaviors, disease prediction, feed formulation optimization, and intelligent decision-making. AI technology, based on information technology, is capable of meeting these needs through data analysis, multidimensional reasoning, and intelligent optimization. As a result, AI has gradually become an indispensable key component in precision feeding systems.

The core of precision feeding lies in providing accurate feed quantities and appropriate nutritional ratios based on the actual needs of individual animals. AI plays a crucial role in this process, particularly in analyzing animal feeding behaviors and integrating health status information for comprehensive management [99]. By leveraging extensive historical data, AI constructs predictive models that include feeding time, amount, and frequency, along with corresponding environmental factors (such as temperature, humidity, and lighting) and the animal's own status (such as age, weight, and health condition). Using machine learning algorithms (e.g., decision trees, neural networks) and deep learning techniques, AI analyzes multidimensional data that encompasses behavioral data (feeding patterns, activity levels, resting postures), physiological data (body temperature, heart rate, respiration rate), and historical disease records [29,30,41,100–102].

On one hand, the models built from these data can precisely uncover patterns/trends in animal feeding behavior and predict nutritional requirements. For example, by analyzing feeding data from dairy cows during different seasons and lactation stages, AI can predict future changes in feed intake [103]. Producers can use these predictions to adjust feeding plans in advance, ensuring they have enough suitable feed ready when a cow's intake is expected to increase, thus meeting the cow's nutritional needs at any given time [104]. On the other hand, AI systems can detect abnormal fluctuations in data and issue early warning signals of potential diseases. For instance, if the activity level of pigs suddenly drops, their feeding behavior becomes irregular (such as reduced feeding time or a sharp decline in feed intake), and their body temperature rises slightly but abnormally, AI can assess that the pigs may be in the incubation or early stages of disease [105]. You et al. used a supervised machine learning approach to detect real-time body weight anomalies recorded by a precision feeding system to automatically feed broilers, breeders, or laying hens based on real-time body weight (BW) measurements [106]. Simultaneously, AI can

adjust the feeding strategy based on the potential impacts of the disease on feeding, such as recommending changes to the texture of the feed, adjusting the nutritional composition, or modifying the feed volume for animals with gastrointestinal issues. This ensures that feeding is always aligned with the animal's current health status, further enhancing the effectiveness of precision feeding.

Throughout the operation of the precision feeding system, AI provides intelligent decision-making and management support in the form of smart software, visualizing complex dynamic aquaculture environments and massive data. Based on predefined farming goals (e.g., improving daily weight gain in beef cattle or ensuring reproductive performance in sows), AI comprehensively considers individual animal differences, current health status, feeding behavior, and the farming environment (e.g., temperature, humidity, air quality), making scientifically sound decisions through intelligent decision-making models [107]. For example, it can determine when to feed animals in different pens in batches, how to adjust feed amounts and feeding times based on weather changes, and more. Additionally, AI provides comprehensive management support for producers, offering visual interfaces that display key data and decision recommendations, allowing producers to easily understand system performance and make effective management decisions. This ensures that the precision feeding system runs smoothly, with precise control at every stage, enhancing farming efficiency and aligning with the core concept of precision feeding: improving farming efficiency, ensuring animal health, and achieving optimal production performance. Figure 6 shows the application of AI technology for poultry.

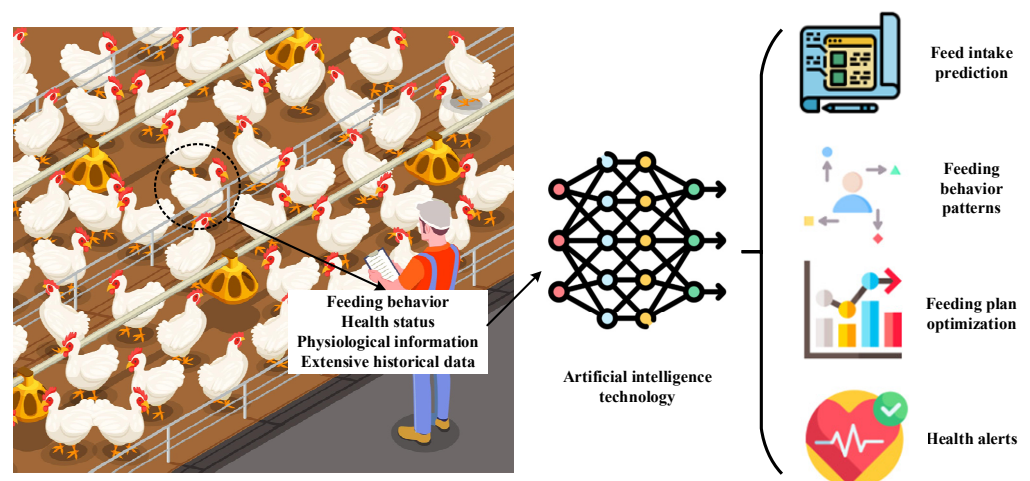


Figure 6. Artificial intelligence technology application (using poultry as an example).

Artificial intelligence is driving the evolution of precision feeding from static empirical decision-making toward dynamic adaptive feeding hubs. However, AI technologies face two core challenges: insufficient decision interpretability and limited scenario adaptability. Black-box models obscure the rationale behind critical strategies (e.g., feed ration reductions), reducing implementation willingness, while models trained for specific scenarios face significant failure risks in divergent farming environments. Future breakthroughs must focus on three areas: (1) developing visual decision-tracing mechanisms to transparently display key variables influencing strategies (e.g., temperature-triggered feeding schedule adjustments); (2) creating scenario-adaptive frameworks enabling rapid rule reconstruction with minimal local data (e.g., self-updating alert logic after inputting novel livestock behavior); (3) establishing human-AI verification protocols requiring manual confirmation for high-risk commands (e.g., abnormal ration reductions). This marks precision feeding's transition into a data-driven, human-AI copiloting paradigm.

4.4. Automated Control Technology

Automation technology is a critical component that spans all stages of the development of precision feeding systems. In the early stages, when comprehensive information and intelligent decision-making data were lacking, basic feeding operations were achieved through simple devices that enabled timed and quantitative feeding. However, as precision feeding systems evolved alongside advancements in sensors, big data analytics, artificial intelligence (AI), and other technologies, automation technology became increasingly capable of refining feeding operations.

In precision feeding systems within livestock farming, the method of feed quantification plays a pivotal role. It is the foundational link through which automation control technology achieves precise feeding, serving as the mechanism for ensuring accuracy. The utilization of weighing-based quantification, facilitated by high-precision weight sensors and control systems, supports the accurate feeding of various livestock species, especially in cases where feed density varies significantly, such as with forage or pelletized feed [108]. In beef cattle farming, the system uses weighing sensors to precisely measure feed quantities according to preset nutritional strategies. The automation control system continuously monitors data from the weight sensors and adjusts the feed dispensing mechanisms accordingly, ensuring that the amount of feed dispensed aligns with the preset target. As the cattle's weight increases, the system dynamically adjusts the feeding strategy, increasing the daily feed amounts to meet the nutritional demands of their rapid growth [109,110]. While volumetric quantification is less precise than weighing-based methods, it offers simpler control and faster efficiency, making it suitable for low-density feeds such as powder, crushed feed, or liquid feed. In the early stages of poultry rearing, chicks have limited feeding capacity and intake. By using containers such as specially sized cups to determine feed amounts, and adjusting container size based on the chicks' age and group size, the system ensures that each feeding is aligned with the chicks' intake needs, promoting uniform growth of the group [111]. Xiong et al. designed a new type of precise feeding control system for lactating sows based on the fixed-capacity approach, which has obvious advantages in cost and is suitable for popularization and application in the lactation workshop of large, medium and small pig breeding farms in China [112]. Jiang et al. achieved precision feeding in rabbit farming using volumetric constant volume combined with robotic arm feeding [113]. Flow-based quantification is more commonly used in pig farming, especially for liquid feed dispensing and mixed feed preparation. For different stages of pig growth—such as for piglets, nursery pigs, and finishing pigs—flow sensors and automation systems precisely regulate the delivery of liquid feed, meeting the animals' varying feeding needs. In mixed feed preparation, accurate control over the flow of raw material pipelines ensures that nutritional components are mixed in precise proportions, providing pigs with a balanced diet that promotes healthy growth and optimal fattening [114].

Feed transmission and dispensing in precision feeding systems serve as the crucial link between the feed source and the feeding endpoints. These systems are closely tailored to the breeding layout and feeding characteristics of different livestock species, resulting in diverse and highly targeted applications [115]. For large-scale sheep farms, conveyor-based feed transmission and dispensing systems are commonly used [116]. The automation control system plans the conveyor routes based on the functional zones of the sheep farm and precisely controls the timing and speed of conveyor operation. For instance, in fattening sheep, which grow quickly and consume large amounts of feed, the conveyor system quickly delivers feed to the dispensing points, where the feeding equipment dispenses feed in a timely and precise manner to meet the nutritional needs of the sheep's rapid growth [117]. In contrast, during special physiological stages, such as pregnancy in breeding ewes, the system adjusts the feed dispensing rate to ensure the feed is delivered slowly and

evenly, supporting both the ewes' health and fetal development. In scenarios involving liquid or powdered feed, pipeline-based feed transmission and dispensing systems offer distinct advantages [118]. For example, in dairy farming, liquid nutritional supplements for cows are delivered through a pipeline system, with automation technology precisely adjusting the pressure within the pipes, the opening and closing of valves, and the operation of pumps to ensure the accurate distribution of liquid feed from the mixing area to the feeding containers in the barns [119]. In poultry farming, crushed feed is transported via pipeline systems to effectively prevent feed waste and environmental contamination due to spillage or dispersal [120]. In egg-laying chicken farms, chain-based automatic feeding machines are used, where small feed cups are moved along a trough by chains [121]. By adjusting the chain speed and feed cup dispensing amounts based on the hens' laying stages, age, and feeding behaviors, the system enables small, frequent, and even feedings, maintaining a consistent feeding rhythm and supporting optimal egg production.

The evolution of precision feeding automation centers on resolving the tripartite tension among accuracy, efficiency, and coordination. In metering systems, gravimetric methods ensure precise proportioning of high-variation forages (e.g., roughages) yet compromise timeliness; volumetric/flow-based methods enhance delivery speed for mash/liquid feeds but suffer from material stability constraints. Conveyance systems must transcend rigid speed limitations: layer chain feeders should dynamically adjust speeds based on pecking behavior while integrating energy-optimization algorithms to minimize idling losses. Distribution terminals require upgrading from passive executors to intelligent closed loops—utilizing sensor networks to locate blockages for autonomous clearance and employing trough-side rapid composition analysis to compensate for ingredient segregation. The ultimate objective is establishing an architecturally integrated control framework: unified communication protocols (e.g., OPC UA) synchronize metering, conveyance, and terminal operations, enabling millisecond-synchronized multi-system switching during growth phase transitions (e.g., weight-gain commands simultaneously triggering ration increases, conveyor acceleration, and trough capacity expansion).

5. Commercial Precision Feeding Systems

Within the scope of precision feeding systems, sensor technology, information technology, artificial intelligence (AI), and automation control technology are the four key general-purpose technologies that jointly form the technological architecture of the system. From a theoretical perspective, the ideal commercial precision feeding system should be a highly integrated product of these four technologies. When they achieve perfect integration, they can create an intelligent and precise “feeding ecosystem” for livestock farming. However, in real-world commercial applications, fully integrating these four technologies presents significant challenges. A series of complex and deep-rooted constraints exists, involving the compatibility and synergy of the technologies themselves. Furthermore, these constraints encompass economic costs, industry standards, and the complexities of practical application environments.

The strategic integration of technologies must fundamentally account for the physical constraints of farming environments, as this constitutes the critical bridge between idealized architectures and commercial viability. The inherent layout variations across livestock facilities directly define the morphological boundaries for technological convergence. This environmental-technological synergy represents the first-principle foundation for constructing viable Feeding Ecosystems. Below we examine commercial implementation pathways for integrated systems across species-specific scenarios.

Cattle barns are typically either open or semi-open, and are divided into dairy barns and beef cattle barns. Dairy barns generally adopt a head-to-head or tail-to-tail layout,

which facilitates milking and management. Beef cattle barns are primarily divided into loose housing or tie-stall systems. Loose housing allows cattle to move freely, while tie-stall systems facilitate individual management and precision feeding. These barns are equipped with spacious feeding areas, and the integration of feeding and pushing tasks by feeding robots has been effectively implemented in such layouts [122]. Feeding robots commonly come in two forms: track-based and self-driving types. Some representative products are listed in the Supplementary Materials (Table S1). Some representative devices are shown in Figure 7.



Figure 7. Goke Livestock Technology Co., Ltd. (Beijing, China) has developed (a) TMR for cattle farming; (b) feeding stations for pig farming; and (c) feeding robots for sheep farming.

Automated feeding in large-scale livestock operations is transitioning from discrete components towards integrated functional terminals. Traditional systems, employing separate ration metering and conveyance units, risk nutrient segregation and stratification during transfer. Total Mixed Ration (TMR) technology addresses this by integrating weighing, homogenization, and targeted delivery within a single terminal, significantly enhancing end-to-end nutritional consistency control [123]. Early cattle feeding systems utilized large-capacity hopper feeders with screw conveyors for handling roughage and concentrates [124]. Automation controls adjust conveyor speed and dispensing based on individual animal behavior, growth stage, and predefined plans, ensuring accurate delivery. TMR equipment is specifically designed for cattle feeding habits and nutritional requirements [125,126], combining roughage (silage, hay), concentrates (grains, proteins), and additives (minerals, vitamins) into a homogeneous, nutritionally balanced mix. This thorough blending prevents selective feeding and ensures consistent nutrient intake per bite [122]. TMR Extension to Herbivores: Equipment is customized based on biological traits. Examples include reduced mixer volumes and pre-cut modules for sheep; non-stick linings and intermittent pulse mixing for high-moisture deer feed; lowered mixing intensity for equine operations; and enhanced liquid dosing for camelids. TMR Principles in Poultry: While traditional TMR equipment is incompatible with poultry, core principles are adapted. Chain-feeding systems incorporate anti-sorting baffles (derived from TMR) to minimize ingredient separation, and mash-mixing processes utilize TMR homogenization techniques to enhance premix uniformity. However, the integrated TMR approach remains constrained for monogastric animals (e.g., swine, poultry) due to incompatibility with their phased feeding regimens.

Modern pig farming typically employs a phase-based, pen-specific feeding model, where piglets, nursery pigs, finishing pigs, and sows are housed separately according to their growth stages and physiological conditions. The number of pigs in each area remains stable. However, the narrow passageways, complex facilities, and intricate layout of pig barns pose challenges. Moreover, pigs at different stages and physiological states have significantly different feed requirements, including both liquid and dry feeds. In this model, fixed electronic feeding stations and feeders offer significant advantages [127,128]. They can precisely adjust feed quantities and feeding times based on the needs of pigs in

different pens, while coordinating with environmental control systems to ensure optimal barn conditions, thereby improving farming efficiency and pig health. Some representative products are shown in Table (in the Supplementary Materials Table S2).

Poultry barns can be divided into flat and multi-tier systems. Flat poultry barns offer a spacious interior where chickens can move freely, with feeding and drinking equipment distributed throughout the barn. Multi-tier systems, on the other hand, maximize space utilization and increase stocking density by employing step-type or stacked chicken cages. Each tier is equipped with independent feeding, drinking, and manure removal systems, making management and automation easier. Commercial feeding equipment for poultry is relatively uniform, primarily consisting of spring auger feeders, pan-type feeders, chain feeders, trolley-type feeders, and scraper feeders [129]. These can accommodate powder feed, pellet feed, and crushed feed, distributing feed evenly to the chickens' feeding positions. For example, the feeding system at Chia Tai (Hong Kong, China) Chongming's 3-million-chicken egg farm project, sourced from Big Dutchman, integrates seven major systems—cage racks, feeding, drinking, ventilation, lighting, egg collection, and manure removal. This system ensures efficient and precise feeding, providing a stable supply of feed and ensuring consistent growth in poultry. Other notable companies include Cumberland Poultry (Shippensburg, PA, USA), Chore-Time (Milford, IN, USA), Vencomatic Group (Eersel, The Netherlands), Jansen Poultry Equipment (Barneveld, The Netherlands), Valco Companies, Inc. (New Holland, PA, USA), OFFICINE FACCO & C. Spa (Campo San Martino, Italy), Jamesway Incubator Company (Cambridge, ON, Canada), Petersime NV (Zulte, Belgium), and ME International Installation GMBH (Achim, Germany) [130]. Domestic companies include Big Herdsman (Qingdao, China) and Shandong Foreway Livestock Technology Co., Ltd. (Linyi, China) [131]. Sheep barns come in various forms, including open, semi-open, and closed types. Common layouts include single or double-row barns with feeding troughs, drinking facilities, and resting areas. Commercial precision feeding systems in sheep farming are less common, with the Total Mixed Ration (TMR) system, commonly used in cattle farming, often being adopted. For example, the feeding robot from China's IMETEC Company uses front and rear lasers for obstacle avoidance, enabling autonomous operation with a slope capability of 0–10% [132]. The ECO automatic lamb feeding system from Aonier, also in China, can accommodate 160–240 lambs per unit [133].

Commercial feeding robots in livestock and poultry farms exhibit complex and multifaceted technological evolution. From a functional perspective, these systems can now integrate multiple advanced technologies to perform highly refined operations. For example, leveraging high-precision animal identification technologies (such as RFID tags or visual recognition), robots can accurately distinguish individual animals. By combining this data with big data analysis of historical growth data, feeding habits, and health status, robots can precisely dispense feed, enhancing the accuracy of feeding. In large dairy farms, feeding systems can even dynamically adjust feed formulas and quantities based on real-time indicators such as milk yield and protein content, a clear demonstration of technological advancement. However, upon closer examination, significant technological bottlenecks remain and require breakthroughs. Although these robots possess a certain level of intelligent decision-making ability, they often rely on preset algorithmic models and limited rule-based judgment. When faced with real-world farming environments with complex and uncertain situations, such as outbreaks of infectious diseases, irregular changes in feeding behavior, extreme weather events, or unexpected issues (e.g., equipment failure affecting ventilation and lighting), robots struggle to make optimal feeding adjustments quickly and accurately. They lack the comprehensive judgment and adaptability that experienced farmers bring to the table. Additionally, the lack of universality and compatibility among different robotic systems is a key issue. Most feeding robots in

the market are designed for specific animal species and fixed farming layouts and scales. Differences in communication protocols, data formats, and hardware interfaces among different brands and types of robots make it difficult to upgrade equipment, expand farms, or change farming models (such as from flat to vertical farming) without substantial human and material resources for system modifications and reconfiguration. In some cases, certain functions may even become incompatible and obsolete, severely limiting the widespread application of this technology.

Cost factors significantly impact the adoption rate of commercial feeding robots. For advanced robots with a variety of intelligent functions, the purchase cost can reach several hundred thousand yuan, which represents a substantial investment for large-scale farms. A careful evaluation of the return on investment and synergy with existing systems is necessary [134]. For small to medium-sized farms, the cost can constitute a major portion of their annual equipment update budget, potentially excluding them from the pool of potential users. Installation costs should not be overlooked, as many farms need to modify their infrastructure to meet the operational requirements of feeding robots, such as power supply, spatial layout, and network communication. This further increases initial costs. More critically, the ongoing operational and maintenance costs are a long-term economic burden. Robots involve complex mechanical structures, electronic components, and software systems that require regular maintenance and updates. These systems need to be operated and maintained by specialized personnel, which adds to the continuous financial strain, especially in an environment where farming profit margins are already limited. This challenge significantly impedes the broader adoption of feeding robots. In addition to cost, the “fit” between farm workers and new technologies is a critical issue. Traditional farming practices heavily rely on experience, and many workers lack sufficient understanding of intelligent feeding robots, their potential benefits, and operational principles. Even when farms acquire robots, workers often struggle to use them effectively without proper training, making it difficult to adjust the robots’ parameters based on real-time conditions. If a robot malfunctions, the lack of troubleshooting skills among farm workers may lead to extended downtimes, impacting normal farming operations. Furthermore, the inadequate marketing and after-sales service systems hinder the widespread adoption of these technologies. Some robot manufacturers invest insufficiently in market promotion, failing to effectively communicate the advantages, features, and real-world applications of their products to farmers, resulting in low awareness and a lack of purchase intent. Additionally, an incomplete after-sales service network makes it difficult for farmers to obtain professional and efficient repair services when robots break down, leading to uncertainty and risk in farm operations and further diminishing confidence in the use of feeding robots, creating a vicious cycle that limits their market penetration.

6. Precision Feeding Systems in Rabbit Farming from Concept to Implementation

6.1. The Necessity of Precision Feeding in Rabbit Farming

Rabbit farming in China has gradually become an integral part of the livestock industry under the promotion of the “big food” concept, with the scale of production expanding steadily [135]. There are both large-scale farming enterprises and numerous small to medium-sized farms [136]. Among them, small to medium-sized farms represent a large proportion but vary significantly in terms of farming technology and management levels. Some still rely on traditional feeding practices, lacking scientific precision feeding awareness and corresponding equipment. Meanwhile, large-scale enterprises have a preliminary understanding of precision feeding and are in the early stages of implementing relevant equipment. Feed costs constitute 52–68% of total rabbit production

expenses, with suboptimal formulations and inaccurate dosing often causing substantial wastage—reaching 20–25% in conventional systems—significantly undermining profitability [137,138]. Precision feeding enhances rabbits’ immune systems, maintains optimal health, and reduces disease incidence. Concurrently, research demonstrates that precision feeding systems can decrease feed wastage by 15–20%, improve feed conversion ratio (FCR) by 10–15%, and enhance overall production efficiency by 12–18% [139–141]. Economic analysis of precision feeding systems in rabbit farming reveals distinct scalability benefits: Large-scale operations (>5000 rabbits) achieve feed savings and labor reduction through automation, with 2–3 year payback periods (Chongqing Fengjie case) [142]. Mid-scale farms (500–5000 rabbits) implementing modular retrofits under 60% policy subsidies shorten ROI, primarily through mortality reduction and accelerated time-to-market (Hubei Xiangyang model) [143]. Smallholders (<500 rabbits) leverage shared-service models to mitigate upfront investment risks, enhancing whole-chain profitability via value-added manure recycling (Ningxia Longde practice) [144].

From the perspective of rabbits themselves, the high fecundity of domestic rabbits (5–8 litters/year, 6–12 kits/litter) [145] fundamentally conflicts with European tiered-cage systems (fattening rabbits in upper cages and integrated doe-kit units below) generating critical challenges: social competition in co-housed units causes nutritional deprivation in submissive individuals; vertical microgradients accelerate feed oxidation in top-tier thermal zones while elevating mycotoxin risks in humid lower cages; circadian disruption occurs as 70% nocturnal nutritional demand (22:00–06:00) remains unmet by diurnal feeding [146]. Crucially, the nutritional divergence—lactating does requiring up to 3× the feed of grow-out rabbits—combined with uniform-tier delivery systems results in significant allocation inefficiency [147,148]. These systemically complex constraints, arising from the coupling of biological imperatives and infrastructure limitations, impose unique operational challenges on precision feeding systems in rabbit farming.

At the same time, rabbits’ physiological and behavioral characteristics make them highly susceptible to environmental disturbances. For example, the sensors required for precision feeding systems and the noise generated by automatic feeding equipment may trigger stress responses, manifesting as reduced feed intake, weakened immunity, or even group panic [149–151]. To avoid these sensitivity and stress-related issues, precision feeding must meet several strict requirements: system design must utilize non-invasive, low-noise equipment; feeding strategies should incorporate gradual adaptation mechanisms to help rabbits reduce their alertness. In summary, the successful implementation of precision feeding in rabbit farming highly depends on the deep integration of technological humanization and animal behavior science; otherwise, the potential efficiency gains may be offset by health losses caused by stress.

6.2. Current Status of Precision Feeding Systems in Rabbit Farming

Europe’s leadership in rabbit farming has driven the development of highly sophisticated precision feeding systems, with commercial solutions showcasing distinct diversification: Germany’s Big Dutchman employs chain/spiral conveyance systems for targeted feed delivery from central silos to cages, augmented by rail-mounted dispensing units enhancing portioning accuracy [152]; the Netherlands’ Fancem utilizes pneumatic pipe conveyance synchronized with programmable control units, integrated with load cells ensuring per-cage ration control [153]; Belgium’s Roxell implements gravity-fed electromagnetic valve systems with timer-photoelectric dual-sensing for anti-clogging monitoring [154]; France’s Hamel leverages RFID-based individual identification to administer stage-specific formula management for does (non-pregnant/gestating/lactating) [155]. While these technologies provide advanced paradigms for China’s industry, Europe’s welfare-oriented model

(e.g., $\geq 0.4 \text{ m}^2/\text{rabbit}$ spatial requirements) fundamentally diverges from China's large-scale production paradigm [156,157]. Our survey of large-scale and small-to-medium-sized livestock farms in China reveals that cost constraints and limited technical awareness have compelled most small/medium operations to retain manual feeding practices, whereas large enterprises have established hybrid systems prioritizing mechanized feeding with manual assistance as supplementary. Precision feeding systems in rabbit production primarily comprise three configurations: Trolley-type feeders operate on overhead tracks to deliver feed across extensive barns, utilizing metering mechanisms for precise portion control per cage or row. This system ensures uniform intake in large-scale operations and accommodates elongated barn layouts effectively [158]. While advantageous for high-throughput facilities, its application is constrained by substantial infrastructure requirements and elevated initial investment, rendering it less feasible for smaller or retrofitted farms. Helical auger feed conveyance systems employ rotating blades within sealed tubes to transport feed, offering structural simplicity and cost efficiency [131]. Their enclosed design minimizes contamination risks, particularly beneficial for fur-bearing breeds requiring hygienic feed handling. Installation flexibility allows adaptation to diverse barn configurations. Limitations include progressive blade wear impairing long-term accuracy, and feed fragmentation during extended-distance conveyance, restricting suitability to small/medium operations. Trough conveyor systems distribute feed uniformly along linear troughs, synchronizing feeding behavior and enabling visual monitoring of consumption patterns [159]. This design aligns with rabbits' natural feeding hierarchies, supporting consistent growth. Operational simplicity facilitates feeding schedule management. Critical constraints involve mandatory residue removal to prevent spoilage-related health hazards, and vulnerability to mechanical failures disrupting feeding cycles. Applicable across farm scales, it prioritizes feeding synchronization over precision dosing. While these precision feeding systems have been proven effective in large-scale or regional feeding, they have not yet been fully integrated with rabbit individual identification technologies. These systems typically feed the same amount to all rabbits in a group, leading to a lack of personalized precision feeding. The next step in implementing precision feeding systems should begin with a comprehensive evaluation of the farm's scale, barn layout, rabbit breeds, and existing infrastructure. Based on the specific conditions of the farm, suitable feeding equipment should be selected. For large farms with well-organized layouts and appropriate track installation conditions, trolley-type feeders should be prioritized. For small to medium-sized farms with limited budgets and flexible barn spaces, spiral auger feeders or long trough conveyor systems may be more suitable. It is also crucial to ensure that the chosen equipment is compatible with future integrations of individual identification systems, sensors, and other technologies, facilitating the creation of a comprehensive precision feeding system.

6.3. Precise Feeding Implementation Framework for Three Stages of Rabbit Farming

Currently, the first stage of precision feeding system development focuses on the integration of feed weighing or quantification sensors. Some large-scale farms in China are already implementing this stage. The application of these sensors is a key step toward achieving precision feeding. Calibrated sensors are installed at critical points in feed storage and transport systems to control the accuracy of feed dispensing. These sensors can precisely regulate the amount of feed dispensed to each rabbit or group of rabbits, minimizing deviations caused by human or equipment errors and improving feed utilization efficiency. In addition, they can monitor the remaining feed levels in the feed trays, enabling farmers to detect any abnormalities in feeding behavior and respond quickly to ensure rabbits' normal feeding and healthy growth [160]. Explore integrating feed ingredient sensors (such

as near-infrared spectroscopy, NIRS) into this stage to monitor real-time fluctuations in feed nutritional indicators (such as moisture content and protein content), providing a more comprehensive data dimension for subsequent precise nutritional regulation. Upgrade from simple weighing sensors to a multi-modal environment-coupled system. Based on this design, establish an open data middleware architecture and adopt modular interfaces to support seamless integration of sensors in subsequent stages. Achieve remote monitoring of equipment status, energy consumption analysis, and predictive maintenance (such as feed line blockage warnings) to reduce operational costs and enhance system reliability. It is recommended to adopt an edge-cloud collaborative computing framework during implementation: edge nodes handle real-time control, while the cloud performs long-term trend analysis, ensuring both response speed and support for big data optimization. Additionally, a sensor drift self-calibration protocol should be established, with regular automatic calibration using standard weights to maintain long-term system stability. The precise feeding quantities, actual consumption data, and timestamps collected during this phase form the most fundamental and critical ‘feed-behavior’ dataset for advanced analyses in subsequent phases, such as individual identification and demand forecasting.

After achieving accurate feed dispensing and collecting feeding behavior data, the next step involves integrating individual rabbit information. Given the realities of large-scale rabbit farming, RFID technology has limitations. These include the small size of rabbits, which makes wearing electronic ear tags uncomfortable and prone to causing damage, as well as the high costs associated with maintaining RFID systems. Therefore, multi-source image sensors and artificial intelligence technologies provide a further solution. This technology deploys multi-spectral imaging modules (visible light + thermal infrared + depth sensing) at key locations on the cage frame, and can even be expanded to include sound acquisition modules, to build a non-contact individual monitoring system. In this process, the installation positions and angles of image sensors must be meticulously designed to ensure the capture of the most accurate and comprehensive data. Concurrently, the application of artificial intelligence (AI) technology plays a critical role in analyzing and processing the vast amounts of image data collected. By identifying individual characteristics and behavioral patterns of rabbits, the feeding system can dynamically and precisely adjust feeding strategies based on the specific needs of each animal. This integration of advanced sensing and machine learning algorithms enables truly individualized feeding, optimizing nutrient delivery while reducing stress-induced deviations in consumption behavior. Specialized lightweight AI models deployed on cameras or edge gateways enable localized real-time individual identification, detection of key behaviors (feeding, drinking, lying down), and preliminary health alerts, significantly reducing data transmission volume and cloud processing latency. Cross-scenario generalization capabilities are built by incorporating domain adaptation technology into model training to adapt to different lighting conditions (e.g., strong summer light/winter supplementary lighting) and cage layout in farming environments. Simultaneously, a behavioral knowledge graph is established to associate specific actions (e.g., increased teeth grinding frequency) with nutritional deficiencies (e.g., insufficient roughage intake), providing semantic support for intelligent decision-making in the third phase. Based on continuously collected individual data, a preliminary ‘digital twin’ is constructed for each rabbit, recording its growth curve, feeding preferences, and historical health events, providing richer individual background information for intelligent decision-making in the third phase.

Building on these two stages, the third stage involves expanding the sensor network to gather data from multiple sources and constructing intelligent decision-making models. These models integrate various data streams and analyze them using advanced AI technologies. They can replace experienced farm experts by providing more comprehensive

analyses of the complex needs of rabbits in different environmental conditions and growth stages. By integrating real-time data, the system can optimize feed nutrient composition, adjust feed amounts dynamically, and arrange feeding times scientifically. This ensures that each rabbit receives the most appropriate feeding plan, achieving efficient operation of the precision feeding system and improving overall rabbit farming productivity and quality. The framework for phased implementation is shown in Figure 8. The implementation requires establishing a closed-loop self-optimizing system that continuously collects model performance feedback (e.g., individual weight gain, health improvements, FCR changes) to automatically refine decision algorithms, enabling autonomous learning and evolution, while developing intuitive visualization interfaces and human-AI copiloting mechanisms that translate complex model outputs (nutrient demand projections, risk alerts, optimization suggestions) into farm-manager accessible formats and generate hypothesis reports for human verification when detecting contradictory signals (e.g., reduced intake with weight gain). This “AI diagnosis + human validation” paradigm leverages algorithmic precision while preserving experiential wisdom. Concurrently implementing blockchain-anchored traceability that immutably records key parameters (feed composition, delivery timing, environmental conditions) in distributed ledgers accessible via product QR codes, and establishing a cross-farm knowledge-sharing platform where privacy-preserved data from multiple farms trains enhanced foundational models through federated learning, democratizing advanced feeding strategies for small-scale operations. It is important to note that the above three-stage framework is a conceptual guidance framework based on the summary of related technologies such as precision feeding in other species, combined with the characteristics of rabbit farming. Currently, China’s precision feeding system for rabbit farming is still in the first stage and has been verified in practice. The latter two stages still need to be verified and analyzed in more detail. However, its technical feasibility has already been realized in other fields.

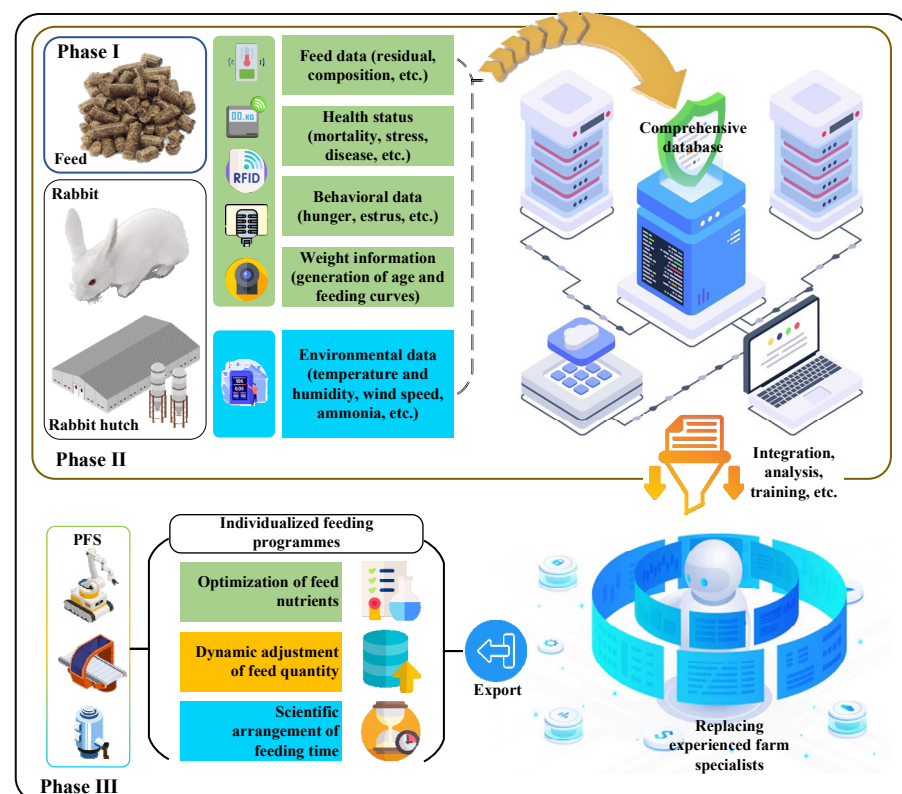


Figure 8. Framework for phased implementation.

To ensure the ongoing effectiveness of the three-stage precision feeding system framework, regular evaluations should be conducted (e.g., monthly or quarterly) to analyze growth performance indicators (e.g., weight gain, reproduction rate, survival rate), feed utilization efficiency (e.g., feed-to-meat ratio, feed conversion rate), and disease occurrence [161,162]. Data comparisons between different stages and batches of rabbits can help identify problems and areas for improvement. Based on these evaluations, adjustments can be made to optimize the system. For example, if growth rates are suboptimal, adjustments to feed formulations can be made, or environmental and feeding conditions can be modified if disease rates are higher in specific areas. The precision feeding system should also be integrated with other farm management systems, such as breeding, disease prevention, and environmental control systems. By enabling data sharing and coordination, a fully integrated intelligent management system can be developed, enhancing overall farm performance and management.

6.4. Feasibility Analysis of a Three-Stage Implementation Framework

This three-phase framework constitutes not a mere adaptation of existing livestock technologies, but a physiology-driven reconstruction of precision feeding logic, meticulously tailored to rabbits' biological vulnerability (stress susceptibility), behavioral uniqueness (high-frequency feeding), and husbandry intensity (multi-tier caging). A comparison of the existing conceptual model with the mainstream precision feeding frameworks for pigs, cattle, and poultry is shown in Table 1. This framework not only fills the gap in precision feeding for rabbits but also provides a universal path for the intelligent farming of small economic animals through its 'contactless individual management + high-frequency dynamic optimization' paradigm.

Table 1. Comparison of precision feeding frameworks for different breeds.

Comparison Dimensions	Cattle	Pigs	Poultry	Rabbits (Traditional)	Rabbits (Three-Stage Framework)
Management unit	Individual (dairy cows)/Herd (beef cattle)	Group (pen system)	Group (cage/free-range)	Group (cage system)	Individual level (AI visual recognition replacing ear tags)
Farming method	Grazing/Confinement	Enclosed pens	Cage rearing/Floor rearing	Multi-tier cage rearing	Cage rearing + dynamic zone monitoring
Lifestyle habits	Gregarious but with high individual space requirements	Gregarious, highly competitive for food	Clear pecking order	Timid and easily stressed, feeds at night	AI identifies stress behavior and adjusts feeding schedule
Feeding habits	Slow eating, rumination	Rapid feeding	Intermittent pecking	Small meals, frequent meals	High-frequency, precise feeding (mimicking natural habits)
Feed differences	Coarse feed-based (TMR)	Pellet/powdered complete feed	Pellets/crushed feed	Pellets (fragile)	Pellet integrity monitoring + anti-waste design
Feeding method	TMR mixer truck/automatic feed hopper	Dry/wet feed hopper/automatic feed dispenser	Chain/disc feeder	Fixed feed hopper	Individual feed box (AI-controlled switch)

To implement the three-phase technical framework, a spiral development methodology is adopted: Phase I (12 months) deploys multi-source sensor networks in pilot farms for system robustness validation; Phase II (6–9 months) integrates vision systems to develop individual recognition algorithms; Phase III (12–18 months) achieves multimodal data fusion and decision model training—each phase incorporates cross-validation checkpoints with a 3-month contingency buffer for extreme conditions, delivering quarterly Minimum Viable Products (MVPs) to ensure controllability. As shown in Figure 9, implementation is scaled by operation size: Small farms (<500 rabbits) adopt lightweight configurations (single

sensor node + 4G edge terminal) with mobile inspection robots ($\approx$ ¥30,000/unit) replacing fixed vision hardware, capping initial investment at ¥80,000. For other modular hardware, the prices of basic temperature, humidity, and weight sensors range from ¥50 to ¥500, while camera sensors range from ¥500 to ¥2000. Mid-scale operations (500–5000 rabbits) implement modular expansion (batch-deployed imaging per barn), sharing regional computing centers and federated blockchain-based disease libraries to reduce server costs; large enterprises deepen three-phase capabilities through unified frameworks enabling vertical compatibility and data synergy, while establishing feedback loops to optimize regional models. All solutions support progressive upgrades from baseline versions, balancing small-farm affordability (entry-level modules) and enterprise data valorization (premium analytics). Concurrently, a tiered training ecosystem is established: L1 equipment operation (AR-guided scanning) → L2 anomaly response (VR fault simulation) → L3 data analysis (expert tele-support), supplemented by multilingual video manuals and a “1 + N neighbor-assist network” (one technician serving five farms).

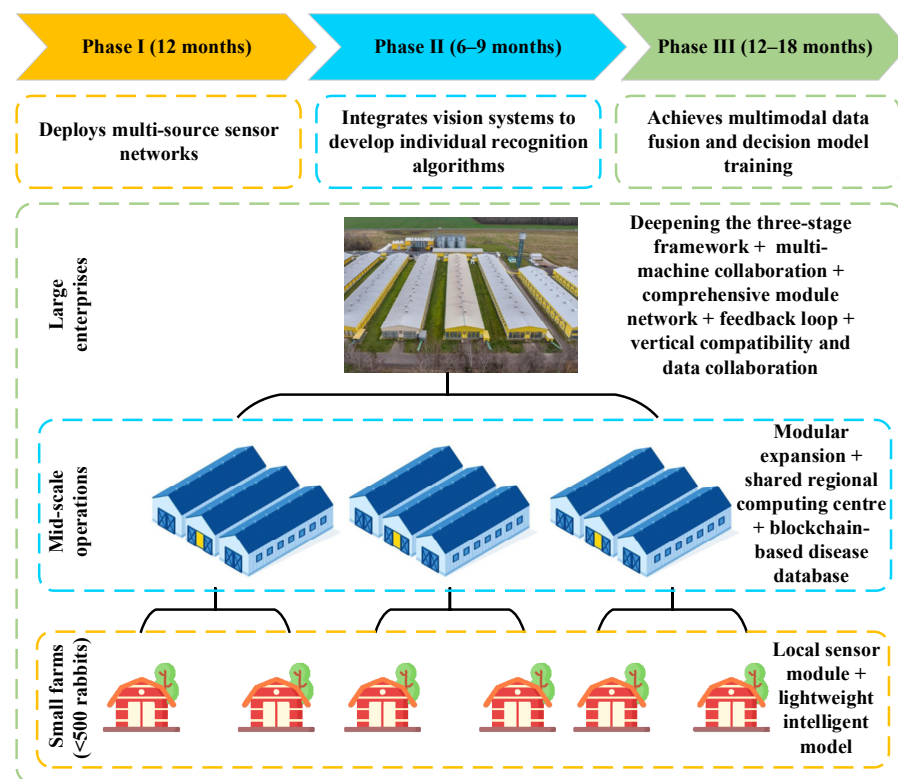


Figure 9. Development cycle for different-sized farms.

6.5. Challenges Facing the Rabbit Farming Industry and Future Development Directions

Beyond the commonly recognized socioeconomic challenges—such as livestock farmers’ generally low acceptance of intelligent technologies due to entrenched traditional empiricism and lack of technical training, alongside the high initial investment costs for intelligent feeding devices and metabolic monitoring systems that deter small and medium-sized farms with limited short-term returns and extended cost recovery periods of 3–5 years—several pressing technical challenges require urgent attention.

Current technical bottlenecks specifically impede rabbit farming applications: (1) Individual Animal Monitoring Difficulties: Unlike larger livestock, rabbits’ relatively small size and group housing conditions complicate the development and deployment of non-invasive, cost-effective sensors for tracking individual feed intake, water consumption, and physiological status in real-time. (2) Data Processing and Model Adaptation: The lack of

robust algorithms trained specifically on rabbit behavioral and physiological data limits the accuracy of existing AI models. Rabbit-specific patterns such as unique feeding behaviors, circadian rhythms, and subtle early disease signs require customized interpretable algorithms that are currently underdeveloped. (3) System Integration and Interoperability: Most available precision feeding systems are designed for larger animals and cannot be directly scaled or adapted to rabbit farming environments without significant hardware and software modifications, creating substantial interoperability barriers. It is worth emphasizing that such technologies can only unleash exponential benefits in long-term, large-scale application scenarios, and through growth cycle optimization, achieve a leap in input-output ratios, forming a sustainable productivity gain loop.

Future development directions should focus on the full-chain penetration of intelligent systems: reducing hardware costs through the development of modular sensors and cloud platform integration, combined with regional demonstration farms and policy subsidies to accelerate technology adoption. A more breakthrough approach lies in integrating blockchain-enabled feed traceability systems (enabling tamper-proof records of feed components, sources, and nutritional ratios) with machine learning-driven dynamic daily feed optimization technology. The latter uses real-time analysis of individual biological characteristics (body weight, activity levels, intestinal biomarkers) and environmental parameters (temperature, humidity) to build predictive models that autonomously adjust nutritional formulas, ultimately achieving individualized nutritional supply. This technological integration will drive the industry's transition from standardized farming to a resource-elastic, adaptable production model, fundamentally restructuring the rabbit industry's value chain.

7. Conclusions

Precision feeding systems (PFS), pivotal for modern livestock farming's efficient and sustainable transformation, leverage sensor technology, information technology (IT), artificial intelligence (AI), and automation control to enable comprehensive monitoring, precise decision-making, and intelligent execution. However, significant technological bottlenecks persist: sensors lack sufficient stability and accuracy in complex environments, demanding miniaturization, intelligence, and integration; IT faces challenges in data security and transmission efficiency amidst growing volumes, requiring optimized data management; AI models exhibit limited real-world adaptability, interpretability, and generalization capabilities; and automation control needs improved equipment stability, accuracy, and optimized algorithms. While commercially deployed, these systems confront hurdles in device/system compatibility, adaptation to diverse farm environments, and cost-effectiveness. With regard to the implementation framework for PFS in rabbit farming, a structured three-stage approach is recommended, emphasizing adaptability to specific farm conditions such as scale, housing type, and breed structure. The first stage focuses on foundational data acquisition through quantified feed dispensing and environmental monitoring, establishing an essential "feed-behavior" dataset. Building on this, the second stage integrates multi-source sensing and lightweight AI models to enable non-contact individual recognition and behavioral analysis, forming the basis for individualized feeding strategies. The third stage evolves into an intelligent decision-support system, incorporating multi-source data fusion, closed-loop self-optimization, and human-AI collaboration to achieve dynamic and adaptive feeding management. This phased pathway underscores scalability and technical feasibility while incorporating modular design and edge-cloud architecture to facilitate seamless integration and system evolution. To ensure functional coherence and operational viability, regular system performance evaluations and deep integration with existing farm management systems are essential throughout the implementation process. The

successful implementation of such measures, particularly in sectors such as rabbit farming, necessitates not only technical customization but also alignment with animal welfare and environmental sustainability principles. Future development should emphasize sustained R&D to overcome existing technical limitations, with application innovations reflecting species-specific and farming-model characteristics. Critically, the evolution of precision feeding must intrinsically integrate animal welfare and environmental sustainability principles, ensuring technological advancement progresses in tandem with animal health and ecological protection, thereby robustly supporting high-quality industry development.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agriculture15212215/s1>, Table S1: Commercial precision feeding systems for cattle farming [163–177]; Table S2: Commercial precision feeding systems in pig farming [178–187].

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