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Review

Digital Twins for Cows and Chickens: From Hype Cycles to Hard Evidence in Precision Livestock Farming

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Abstract

Digital twin technology is widely promoted as a transformative step for precision livestock farming, yet no fully realized, engineering-grade digital twins are deployed in commercial dairy or poultry systems today. This work establishes the current state of knowledge on dairy and poultry digital twins by synthesizing evidence through systematic database searches, thematic evidence mapping and critical analysis of validation gaps, carbon accounting and adoption barriers. Existing platforms are better described as near-digital-twin systems with partial sensing and modelling, digital-twin-inspired prototypes, simulation frameworks or decision-support tools that are often labelled as twins despite lacking continuous synchronization and closed-loop control. This distinction matters because the empirical foundation supporting many claims remains limited. Three critical gaps emerge: life-cycle carbon impacts of digital infrastructures are rarely quantified even as sustainability benefits are frequently asserted; field-validated improvements in feed efficiency, particularly in poultry feed conversion ratios, are scarce and inconsistent; and systematic reporting of failure rates, downtime and technology abandonment is almost absent, leaving uncertainties about long-term reliability. Adoption barriers persist across technical, economic and social dimensions, including rural connectivity limitations, sensor durability challenges, capital and operating costs, and farmer concerns regarding data rights, transparency and trust. Progress for cows and chickens will require rigorous validation in commercial environments, integration of mechanistic and statistical modelling, open and modular architectures and governance structures that support biological, economic and environmental accountability whilst ensuring that system intelligence is worth its material and energy cost.

Keywords: digital twins; livestock farming; hybrid modelling; computer vision; feed efficiency; livestock sustainability; poultry behavior

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1. Introduction

Livestock agriculture stands at the centre of profound demographic, environmental and ethical pressures that shape the trajectory of global food systems. Rapid population growth, projected to approach 9.7 billion by mid-century, is expected to increase demand for animal-sourced foods, even as resource limitations and climatic instability constrain the capacity of production systems to respond effectively [1]. Livestock are already responsible for a substantial share of anthropogenic greenhouse gas emissions, with ruminant methane and manure-derived nitrous oxide recognized as significant hurdles for meeting international climate targets [2]. Although poultry systems generate comparatively lower

methane emissions, their environmental burdens remain considerable due to feed production, manure management and energy use, and they are further complicated by welfare concerns and recurring vulnerability to diseases such as avian influenza [3]. These tensions have intensified interest in developing technological strategies that enhance productivity, resilience, welfare and sustainability while navigating the constraints imposed by biological variability and economic realities.

Over the past three decades, precision livestock farming has emerged as one response to these pressures, advancing from isolated sensor systems toward more integrated, data-enriched approaches to husbandry. In dairy production, early innovations centred on single-modality devices such as pedometers and neck-mounted accelerometers for estrus detection, in-line milk meters for continuous yield recording and research-grade rumen pH boluses designed to study subacute ruminal acidosis [4]. These systems produced discrete indicators that supported specific management decisions but offered only partial representations of animal status. Poultry applications began with simple environmental controllers linked to temperature and humidity probes, alongside weighing platforms used to estimate flock mass. Behavioural or welfare measurements were limited, reflecting both the scale of commercial poultry houses and the perceived complexity of monitoring individuals within large flocks [5].

As sensing technologies became more affordable and computational capacity increased, multimodal monitoring platforms emerged across both species. Dairy operations began integrating accelerometers, rumination microphones, thermal imaging and milk conductivity sensors, enabling more comprehensive assessments of physiology and behaviour [6]. In poultry houses, high-resolution cameras, dense environmental sensor arrays and microphone networks capable of capturing vocalization patterns associated with stress or respiratory disturbances were deployed, providing new avenues for inferring flock-level states [7]. These developments marked a significant shift from isolated measurements toward richer, continuous data streams that could describe animals and environments with increasing granularity.

The conceptual leap toward digital twins occurred when these multimodal sensor platforms were re-imagined as the perceptual layer of virtual counterparts of animals or facilities. Digital twins, originally defined in aerospace engineering, describe continuously updated virtual entities that remain tightly coupled to their physical versions through live data streams [8]. The application of this concept to livestock systems gained traction as researchers recognized that established nutrition, growth and disease-risk models—long used in the dairy and poultry sciences—could serve as the computational engines of these virtual organisms or virtual barns [9]. In this framing, a digital twin assimilates behavioural, physiological and environmental data, updates latent states, supports scenario analysis and informs decisions aimed at improving health, welfare or system performance.

Analogous developments in industry have further catalyzed interest in agricultural digital twins. In advanced manufacturing and aerospace, digital twins have transitioned from experimental frameworks to operational tools used for structural monitoring, production optimization and life-cycle assessment [10]. Their success has been facilitated by standardized architecture, verification protocols and reporting of system reliability and environmental impacts. The attractiveness of these industrial precedents has led agricultural researchers to explore comparable models adapted to biological systems. Reviews focused on smart farming and Agriculture 5.0 highlight the significant potential of digital twins, but they also underscore the technological, infrastructural and methodological gaps that currently limit their adoption in livestock systems [11,12].

Despite these limitations, digital-twin narratives have diffused rapidly through the livestock sector. They now appear in conference presentations, industry white papers

and strategic planning documents, often framed as the logical next evolution of precision livestock farming [13], yet most implementations remain at the prototype or pilot stage, with notable challenges in interoperability across sensor vendors, inconsistencies in data quality and a scarcity of long-term validation studies that could demonstrate robust performance in real commercial environments [14]. These challenges underscore the inherent complexity of biological systems and the difficulty of translating digital-twin concepts from engineered domains to dynamic, heterogeneous livestock settings.

Awareness of this complexity has motivated efforts to position livestock digital twins within broader frameworks of technological development, including the Gartner hype cycle. Early enthusiasm was driven by demonstrations that computer vision, accelerometry and environmental sensing could outperform human observation in detecting health or welfare deviations [7]. This enthusiasm contributed to a peak in expectations in which digital twins were credited with the potential to deliver large gains in efficiency, major reductions in environmental impact and near-perfect predictive accuracy, often extrapolated from controlled experiments or simulation studies. More recent work has tempered these claims, documenting the fragility of sensor networks in harsh barn environments, the difficulty of integrating heterogeneous data systems and the gap between performance in laboratory conditions and commercial practice [14]. These findings suggest that livestock digital twins are entering a period in which inflated expectations must be recalibrated toward achievable, evidence-supported value propositions.

A further complication arises from the inconsistent use of the term "digital twin" across agricultural research and industry. Some systems labelled as digital twins are, in practice, sophisticated dashboards that aggregate sensor data without mechanistic modelling or feedback control. Others function as simulation tools only loosely connected to live data. In engineering, a digital twin is defined by persistent synchronization between virtual and physical systems, dynamic state estimation and the ability to evaluate alternative interventions that influence real-time management decisions [8,10]. Translating this definition to livestock farming implies a virtual dairy cow or flock that assimilates continuous behavioural, physiological and environmental data, updates predictions regarding health or performance and simulates the consequences of alternative feeding, stocking or climate-control decisions. Distinguishing such fully coupled digital twins from simpler monitoring platforms is essential because their validation requirements, reliability expectations and ethical implications differ substantially.

The challenges and opportunities associated with digital twins differ markedly between dairy and poultry production systems. Dairy cows are long-lived, high-value animals with chronic health challenges including mastitis, lameness and metabolic disorders. These constraints justify relatively sophisticated instrumentation such as rumen boluses, activity sensors and in-line milk analyzers, which generate rich longitudinal datasets suited to individual-level modelling and decision support [4]. Digital twins in dairy therefore emphasize individual trajectories, including early detection of subclinical disease, optimization of feed efficiency and modelling of methane emissions grounded in metabolic physiology [15]. Poultry production, by contrast, involves short-lived, low-value animals managed in large, uniform flocks. Disease risks are often acute and rapidly spreading, management decisions occur at the flock scale and performance metrics such as the feed conversion ratio dominate economic outcomes [3,5]. Consequently, poultry digital twins focus on flock-level dynamics, disease incursion and spread, barn microclimate regulation and feed efficiency, drawing heavily on computer vision and environmental sensing [7,16].

These two species were selected as comparative case studies because they represent the biological and economic extremes of livestock production: dairy cattle as high-value, long-lived individuals requiring precision management, and poultry as low-value, short-

lived populations managed as aggregate biological systems. This contrast allows for a comprehensive examination of how digital-twin architectures must adapt to opposing constraints of scale, unit value and physiological complexity. These structural contrasts shape how technological claims should be evaluated. In dairy systems, assertions regarding improved mastitis detection, ration precision or methane mitigation require demonstration of long-term, animal-level benefits. In poultry systems, claims of enhanced feed conversion or reduced mortality require evidence across multiple production cycles, housing conditions and seasons. Overstatement risks eroding trust among early adopters, slowing the broader adoption of data-driven livestock technologies [14].

The aim of this study is to clarify the current position of digital-twins for cows and chickens along the continuum from conceptual construct to practical, validated technology. Through analysis of historical developments in precision livestock farming, comparison of structural and biological differences across species and synthesis of how digital-twin concepts have evolved across research and commercial narratives, this study seeks to distinguish verifiable capabilities from aspirational rhetoric. The scope of digital twin development in livestock, spanning engineering theory, empirical field work, simulation studies and commercial narratives, transcends a discrete research question addressable through systematic review. This analysis instead synthesizes across heterogeneous literatures through interpretive integration and critical appraisal, structured by explicit database searches, systematic screening and thematic evidence mapping. The overarching objective is to outline how livestock digital twins can advance toward systems that are biologically meaningful, economically viable and environmentally accountable.

2. Materials and Methods

2.1. Databases and Thematic Queries

The methodological strategy was developed to build a comprehensive and thematically structured body of evidence spanning both dairy cattle and poultry systems, reflecting the dual focus of this study on cows and chickens. The search was intentionally organized around four empirically tractable questions that interrogate key dimensions of digital-twin readiness in livestock. These questions addressed the carbon footprint of digital agriculture infrastructures deployed in livestock environments, the extent of field-validated improvements in poultry feed conversion ratio attributable to digital decision systems, the performance assessment frameworks proposed or applied to livestock digital twins and the reported failure rates, data quality degradation, downtime and abandonment associated with precision livestock technologies.

To address these themes systematically, searches were conducted across Web of Science Core Collection, Scopus, PubMed, ScienceDirect, IEEE Xplore and Google Scholar, complemented by Semantic Scholar and OpenAlex. Query strings were designed to retrieve studies involving dairy cattle, beef cattle, broilers, layers and cross-species frameworks explicitly intended for livestock. For the carbon-footprint theme, search expressions combined descriptors of digital agriculture with life-cycle assessment concepts and digital-infrastructure terms capable of capturing analyses of sensor systems, embedded controllers and cloud-based platforms used in cattle barns and poultry houses. For the feed-conversion theme, queries combined digital twin, cyber-physical system and adaptive-control terminology with species-specific descriptors for broilers and laying hens and with performance indicators related to feed efficiency. These were supplemented with adaptive-control terminology to identify studies in which digital systems influenced growth trajectories or microclimate regulation.

The performance-framework theme required broader cross-sectoral expressions because many maturity models and evaluation frameworks originate in manufacturing or

process-industry domains before being adapted to livestock contexts. Combinations of digital-twin terminology with performance and evaluation descriptors were used to retrieve frameworks that could plausibly apply to dairy and poultry systems. The failure-and-abandonment theme emphasized operational fragility and searched for descriptions of reliability, downtime, sensor degradation, signal loss and data-quality problems across both dairy and poultry deployments. Because reliability information is often embedded within methodological notes rather than indexed in titles or abstracts, semantic search functions within the Elicit platform were used to identify studies containing discussion of "missing data," "sensor drift," "signal instability" or "system downtime."

All search activities were restricted to publications in English published between January 2015 and November 2025 to capture the period during which sensor-dense livestock systems and digital-twin concepts became technically feasible. The entire search strategy was cross-checked against existing surveys of digital systems in dairy and poultry to minimize the risk of missing known landmark studies. All search strings were constructed to capture both ruminant systems centred on dairy cows and monogastric poultry systems including broilers and laying hens, reflecting the dual focus of this study on cows and chickens.

2.2. Screening and Study Selection

The combined database searches returned approximately 2000 unique records after deduplication. Screening followed a two-stage procedure aligned with PRISMA principles. In the first stage, titles and abstracts were evaluated to remove studies clearly outside the domain of livestock production, including applications in industrial engineering, crop-only digital systems and generic Internet of Things deployments without modelling or decision-support components. Conceptual and review papers were retained if they related to either dairy or poultry and contributed to at least one of the thematic questions. After this stage, 350 to 400 records remained.

In the second stage, full-text screening was undertaken using more stringent inclusion criteria. Studies were retained if they described digital, cyber-physical or near-digital-twin systems applied to dairy cattle or commercial poultry, or frameworks explicitly spanning these two species groups. Each study needed to incorporate at least two of three elements—multimodal sensing, a dynamical or statistical modelling component and some form of decision support or automated control. For the feed-conversion and system-failure themes, studies needed to report quantitative endpoints such as feed conversion ratios, mortality, downtime or data-discard rates. For carbon-footprint analyses, studies needed to quantify greenhouse gas emissions or related environmental indicators attributable to digital or sensing infrastructures rather than whole-farm management. Papers outlining purely aspirational visions without technical detail were excluded.

Approximately 200 full-text articles were examined in depth. Following full-text screening, 104 studies met the inclusion criteria and were retained for structured evidence synthesis. Of these, the majority focused on a single production domain, with studies addressing either dairy cattle or poultry systems, while a smaller subset proposed cross-species or generic digital-twin frameworks. Only a limited fraction of included studies reported quantitative field validation under commercial farming conditions, and systematic reporting of system reliability, downtime or failure rates was rare. A complete breakdown of included studies by species focus (dairy, poultry or cross-species), study design, validation context and reporting of quantitative outcomes is provided in Table S1. Table S2 further maps digital-twin and twin-inspired implementations to support cross-species comparison and assessment of evidence maturity. The final dataset therefore included empirical field trials in commercial dairy barns and poultry houses, simulations driven by real farm data,

case studies of digital deployments and conceptual analyses clarifying system architecture or adoption patterns. Accordingly, this review combines narrative synthesis with scoping-style evidence mapping rather than adhering to a formal systematic review protocol. Table 1 provides a summary mapping of these 104 included studies by species, system archetype, study design and endpoint, illustrating the distribution of evidence.

2.3. Data Extraction and Risk of Bias

Data extraction was carried out using a structured template capturing system-level, design-level and outcome-level information across both dairy and poultry studies. Species was coded as dairy, poultry or mixed, enabling separate synthesis for cows and chickens as well as integrated interpretation where cross-cutting themes emerged. System-level fields captured species and production system (such as free-stall Holstein barns, pasture-based dairies, commercial broiler houses and enriched-cage layer facilities), scale of deployment, sensor types and placement, data sampling frequency, data-pipeline architecture and the modelling approach used by the system. Design-level fields captured study duration, number of animals or houses, the structure of comparison groups, whether randomization or blinding was present and whether trials spanned single or multiple production cycles.

Outcome-level fields recorded all quantitative metrics relevant to the four thematic strands. For health-focused dairy systems, extracted metrics included sensitivity, specificity, predictive value and detection lead time. For nutrition and feed-conversion analyses in both cattle and poultry, recorded metrics included FCR, feed intake, weight gain, milk yield or egg production. Environmental and microclimate systems contributed data on temperature and humidity regulation, energy consumption and, when available, emissions estimates. Reliability metrics captured device failure rates, signal-loss events, percentages of discarded data, system downtime and maintenance load. When reported, economic indicators and farmer experiences, including perceived usefulness and trust, were noted to contextualize feasibility in both dairy and poultry settings.

Heterogeneity in study designs precluded the use of a single formal risk-of-bias tool. Recurring sources of bias included publication bias due to the scarcity of negative results, geographic skew arising from regional concentration of certain technologies, vendor involvement that limited independent benchmarking and conceptual heterogeneity in which disparate systems were labelled as digital twins. Short follow-up periods and single-cycle evaluations were common, reducing the ability to assess stability across seasons or production cycles. These considerations informed subsequent analysis and interpretation of the evidence regarding the current state of digital-twin development for dairy and poultry production systems.

2.4. Limitations of This Approach

Several limitations warrant explicit acknowledgment. Publication bias remains a concern, as positive results, novel prototypes and successful implementations are preferentially published relative to failures, abandonment and negative findings. Language restrictions to English-language publications may exclude relevant research from regions where digital livestock technologies are advancing rapidly. The absence of formal risk-of-bias assessment tools limits quantitative weighting of evidence quality; instead, recurring sources of bias are discussed qualitatively in Section 2.3. Finally, interpretive synthesis necessarily involves author judgement in selecting, organizing and critiquing evidence. These limitations are inherent to the approach and are balanced by its strengths in breadth of coverage, integration of diverse evidence types and critical engagement with tensions that would remain obscured in narrower methodological frameworks.

2.5. Result Mapping

The findings presented in the Results Section are organized according to the four thematic strands that shaped the search strategy and screening process. Evidence for each theme is synthesized separately for dairy and poultry systems, with cross-species patterns highlighted where relevant. Quantitative outcomes for health, nutrition, environmental performance and reliability are mapped against the system-level and design-level characteristics captured during data extraction, allowing identification of recurring strengths, gaps and methodological limitations. This structure enables a coherent comparison of digital-twin maturity across cows and chickens, clarifies where evidence clusters and reveals where robust field-validated data remain sparse.

3. Architecture and Enabling Technologies

Digital twins for cows and chickens can be conceptualized as layered cyber-physical systems that couple sensing, computation, modelling and decision support into a continuously updating representation of animals and their environments. For clarity, this review organizes livestock digital-twin architectures into five layers: sensing, edge and cloud data pipelines, models, control and optimization and interfaces and human interaction [17–19]. Each layer raises distinct design questions and is illustrated here (Figure 1) with concrete examples from dairy and poultry systems [17–20].

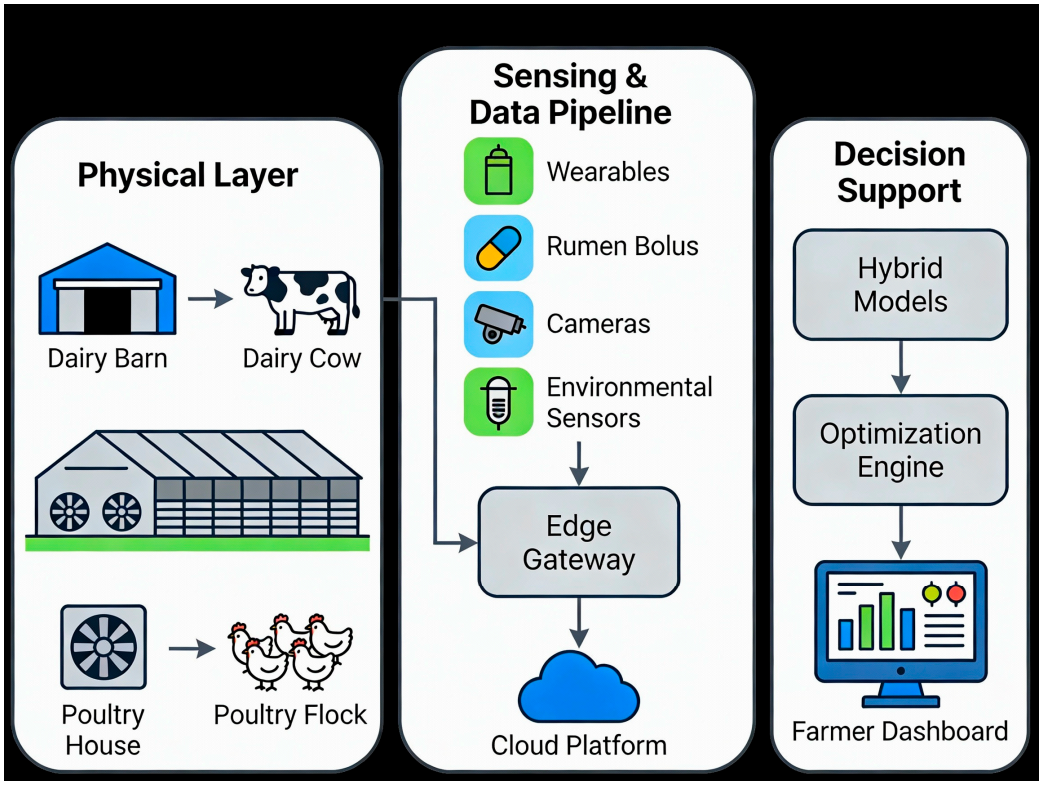


Figure 1. Schematic architecture of a livestock digital twin for dairy and poultry. The physical layer (**left**) generates biological and environmental signals captured by the sensing and data pipeline (**middle**). Raw data from wearables, boluses and cameras is aggregated via edge gateways and transmitted to the cloud. The decision support layer (**right**) processes this data using hybrid mechanistic and AI models to generate optimization insights and alerts, displayed on a unified farmer-facing dashboard.

3.1. Layer 1: Sensors and Data Acquisition

The sensing layer provides the raw material from which digital-twins are constructed. In dairy systems, sensors now include on-animal, in-animal and in-barn devices that capture behaviour, physiology and the microclimate at high temporal resolution. Wearable accelerometer collars and leg tags quantify activity, lying duration and step counts and can infer rumination time through acoustic or vibration signatures. These signals form key inputs to the behaviour and health modules of dairy digital twins. Ingestible rumen boluses have progressed from research prototypes to commercially deployed devices capable of measuring internal temperature and pH over multiple years, providing a stable, long-term sensor node within the virtual representation of the cow. Continuous internal temperature and pH profiles can reveal drinking events, changes in feed intake, heat stress and inflammatory processes, all highly relevant latent states for digital twin models. Milking robots and parlour systems generate high-frequency data on milk yield, electrical conductivity, flow curves and, in some systems, mid-infrared spectra that provide information on udder health, metabolic status and energy balance. Barn-level sensors measuring temperature, humidity, ammonia and carbon dioxide complement animal-centric data and are essential for linking cow responses to environmental conditions.

In poultry, low unit value and high stocking density limit individual instrumentation, so sensing strategies focus on environmental and flock-level observation. Smart poultry houses deploy networks of temperature, humidity and gas sensors alongside static or pan–tilt cameras that capture flock distribution, movement and surface behaviour. Several frameworks integrate camera, microphone and gas-sensor stacks to monitor behavioural and environmental indicators concurrently [21–27]. Cameras track dispersion and locomotion, microphones capture vocalization patterns and respiratory sounds, and gas sensors quantify air quality and ventilation effectiveness. Recent poultry digital-twin frameworks describe such multimodal sensing as the perceptual system of the virtual poultry house, enabling the twin to infer welfare and health states from spatial, behavioural and acoustic patterns.

Despite these advances, sensor deployment in commercial barns remains challenging. Dust, moisture and ammonia cause sensor drift and failures, and animals or equipment can damage cables and devices. Wireless signals become attenuated around metal structures and dense flocks, generating blind zones and intermittent connectivity. Field studies in broiler and layer facilities report substantial proportions of unusable data due to missing timestamps, duplicated records or out-of-range values, highlighting the need for robust preprocessing and data-quality monitoring within the twin architecture.

3.2. Layer 2: Edge Computing, Cloud Infrastructure and Data Pipelines

The second layer concerns the movement, aggregation and initial processing of sensor data. Dairy and poultry farms often experience constrained connectivity, making edge and fog computing essential design choices. In dairy barns, data from collars, boluses and milking equipment are captured by local gateways that perform time synchronization, filtering, basic feature extraction and compression before transmitting summaries to a farm server or cloud platform. This reduces bandwidth requirements and enables critical alerts such as calving suspicion, mastitis risk or abnormal rumination to be generated even when connectivity is intermittent.

In poultry houses, the volume of image and audio data makes full-resolution streaming impractical and often unnecessary [25–27]. Edge devices equipped with GPUs or NPUs can run computer vision and audio-classification models locally, extracting higher-level features such as flock activity indices, density maps or cough-event counts. These features are then forwarded to central servers or cloud platforms. Fog architectures distribute

computation across barn-level nodes and a farm-level gateway, allowing multiple houses on a complex to share processing resources and synchronize their virtual models while maintaining local responsiveness.

Data pipelines must also manage heterogeneity and interoperability. Livestock facilities commonly mix sensors and equipment from different vendors, each using proprietary communication protocols. Without harmonization, the integrative potential of digital-twins is undermined. Recent open frameworks, such as generic agricultural digital twin architectures and open-source farm-twin platforms, propose standardized data models and APIs to integrate heterogeneous sensor streams and external data sources. However, adoption remains limited, and many commercial deployments still rely on bespoke integrations that complicate scaling and cross-farm comparison.

However, this architectural shift introduces new sustainability trade-offs. While edge processing reduces the energy intensity of data transmission, the proliferation of GPU-equipped edge devices increases the embodied carbon footprint of the barn's digital infrastructure. Recent Green AI analyses suggest that the energy cost of manufacturing and operating distributed edge nodes can only be justified if they enable critical real-time decisions that significantly improve production efficiency or welfare, rather than simply accumulating redundant data.

3.3. Layer 3: Mechanistic, Statistical and Hybrid Models

The modelling layer transforms sensor data into estimates of latent states and predictions of future trajectories. In dairy systems, digital twins draw on mechanistic nutrition and physiology models such as the Cornell Net Carbohydrate and Protein System and the NASEM nutrient-requirement models. These frameworks describe how feed intake and composition are partitioned into maintenance, growth, pregnancy, lactation and body reserves. They can be parameterized using individual characteristics such as body weight, parity, days in milk and milk composition, then updated continuously with observed behaviour and production to estimate dynamic energy balance and metabolic risk.

For health monitoring, statistical and machine learning models are increasingly used to predict events such as mastitis or lameness from multi-sensor time series. Studies using combinations of milk yield, electrical conductivity, activity, rumination and internal temperature have reported sensitivity exceeding 80 to 90 percent, demonstrating the potential for early, model-based alerts within dairy digital twins. Rumen-bolus data have been used to characterize drinking behaviour, detect fever and identify digestive disorders before clinical signs, providing an additional data stream that feeds probabilistic estimators of health states.

In poultry, modelling focuses on growth, thermal comfort and flock-level performance [25–27]. Broiler growth curves are often modelled with Gompertz or logistic functions that can be updated dynamically with inline or platform weight measurements. Thermal comfort models link temperature, humidity, airflow and age to welfare indices, mortality risk and growth performance. FCR trajectories are modelled using time-series or machine learning approaches that relate feed use and weight gain to microclimate and management variables. Recent poultry digital twins combine these growth and climate models with computer-vision-derived indices such as spatial uniformity and resting behaviour, creating richer virtual representations of flock state.

Hybrid modelling that combines mechanistic structures with machine learning is emerging as a promising direction. Mechanistic thermophysiological models can provide physically plausible bounds for learning algorithms, improving robustness under heat stress or unusual conditions. Similarly, mechanistic rumen or digestion models can

constrain learning-based intake predictions and health-risk estimations, enhancing interpretability for farmers and veterinarians.

3.4. Layer 4: Control and Optimization

The fourth layer translates model outputs into actions, closing the loop between virtual predictions and farm management. In dairy systems, most commercial applications remain at the level of alerts and recommendations, flagging animals at risk of mastitis, identifying cows in estrus or suggesting ration changes. Some components already support semi-automatic control, such as dynamic concentrate allocation systems that adjust individual feed levels in real time based on predicted energy balance, milk yield and days in milk. A fully realized dairy digital twin could simulate alternative feeding or grouping strategies and recommend those that optimize production, health and emissions under specified constraints.

In poultry houses, closed-loop control is more advanced in climate and feeding systems [25–27]. One digital system in commercial broiler houses combined long short-term memory neural networks with a genetic algorithm to generate daily action plans. The system predicted outcomes such as feed conversion ratio and mortality under different ventilation and feeding strategies, then selected plans that improved performance while respecting operational constraints. In field trials, this digital system achieved improved FCR compared with specialist-configured conventional plans, illustrating the potential of digital-twin-style control strategies.

Optimization in both species is inherently multiobjective, requiring trade-offs between production, welfare, environmental impact and economic performance. Multiobjective optimization algorithms and model predictive control frameworks are therefore natural tools within this layer, especially when coupled with scenario analysis for robustness under uncertainty in feed prices, weather patterns or emerging health risks.

3.5. Layer 5: Interfaces, Visualization and Human Interaction

The fifth layer concerns the interfaces through which farmers, veterinarians and advisors engage with the digital twin. Interface design strongly influences adoption and effective use. Dashboards designed primarily by engineers may expose technical metrics and dense time-series plots that overwhelm farm managers. Farmer-centred design consistently emphasizes the need for simple, actionable information such as clear alerts, prioritized task lists and concise explanations.

In dairy systems, dashboards commonly present lists of animals requiring attention with options to inspect underlying sensor trends. Digital twins can extend this by visualizing predicted trajectories, such as projected milk yield under alternative feeding strategies, and by providing interactive tools to explore hypothetical scenarios. Early work on augmented reality suggests the possibility of future interfaces in which farmers viewing a pen through a tablet or smart glasses could see twin-derived indicators, such as health risks or environmental stress, superimposed on the physical scene.

In poultry houses, dashboards summarize temperature, humidity, ammonia concentration, feed and water consumption and computer-vision-derived activity indices [25–27]. When embedded within twin frameworks, these dashboards can show predicted effects of modifying set points or stocking density, helping managers evaluate trade-offs between growth, welfare and energy use. Studies of farmer attitudes indicate concerns about opacity and over-reliance on black-box systems, highlighting the importance of explainability. Trust is strengthened when systems provide interpretable rationales for alerts, rather than opaque notifications.

4. Dairy Applications

While the architectural layers described in Section 3 provide the necessary technical foundation—sensing, connectivity, modelling and control—their practical implementation differs fundamentally between species. The high individual value of dairy cows justifies the complex, animal-centric sensor stacks (Layer 1) and individualized metabolic models (Layer 3) previously discussed. Consequently, dairy digital twins have evolved primarily as tools for managing individual physiological trajectories, focusing on health events and reproductive status that drive unit-level profitability. This contrasts with the flock-level focus of poultry systems (detailed in Section 5), illustrating how biological constraints dictate digital-twin design.

4.1. Health Monitoring and Mastitis

Digital twins for dairy cows build on disease-detection capabilities developed within precision monitoring systems, with mastitis serving as a central test case due to its prevalence and economic significance. Machine learning models trained on multi-sensor data, combining milk yield, electrical conductivity, milking interval, activity, rumination and internal temperature, consistently outperform single-indicator thresholds for mastitis detection [28,29]. Recent studies using on-farm sensor streams reported sensitivities above 80 to 90 percent and specificities between 70 and 85 percent when evaluated against veterinary diagnoses or somatic cell count thresholds [30]. These models commonly apply logistic regression, random forests or gradient-boosted trees, and more recent work explores deep learning architectures capable of capturing complex temporal patterns in milk and behaviour data.

Rumen-bolus technology extends health monitoring into the internal environment of the cow. Continuous intra-ruminal temperature and pH records allow detection of drinking events, circadian rhythms and deviations associated with inflammation or digestive disturbance. Studies show that sustained elevation of rumen temperature above individual baseline values can precede clinical signs of fever and reduced intake, providing early warning of infectious disease, while prolonged pH depression signals risk of subacute ruminal acidosis [31,32]. When bolus data are fused with behavioural and milk-production traits, the resulting multimodal profiles support estimation of latent health states, such as subclinical inflammation or digestive instability, that influence disease risk and performance loss [33].

Together, these elements form the health core of a dairy digital twin. The twin assimilates continuous streams from milking systems, wearables and rumen boluses, uses trained classifiers to estimate probabilities of mastitis or acidosis and projects the likely impact on milk yield and welfare if no intervention occurs. Instead of relying on single thresholds, the twin maintains an evolving, individualized baseline for each cow and flags deviations that are statistically unlikely given her history and physiology. Such a twin can also simulate intervention scenarios, such as early treatment, modified milking frequency or ration adjustment, and present predicted trajectories to the farmer, shifting mastitis management from reactive treatment toward proactive risk mitigation.

4.2. Metabolic and Reproductive Health

Digital twins can strengthen monitoring of metabolic and reproductive disorders that cluster around the transition period and early lactation, when cows experience negative energy balance and heightened disease susceptibility. Subclinical ketosis, displaced abomasum and fatty liver are often preceded by characteristic changes in intake, activity and milk composition that are difficult to discern without integrated analytics. By combining rumination time, lying behaviour, activity indices, milk fat-to-protein ratio and internal

temperature, models can estimate daily energy balance and assign risk scores for metabolic disease, enabling earlier intervention or nutritional adjustment [33].

Estrus detection remains a major application of activity monitoring, and digital twins provide a framework for integrating multiple signals to improve timing and reliability. Accelerometer collars and leg-mounted sensors capture increased locomotion during oestrus, while rumination typically declines. When combined with subtle shifts in milk yield and, where available, hormone proxies, estrus-detection algorithms can achieve sensitivities above 80 percent with acceptable false-positive rates [34,35]. Embedding these models within a twin allows predictions to be contextualized by parity, days in milk, fertility history and current metabolic state, generating more nuanced recommendations, for example, distinguishing cows physiologically ready for breeding from those expressing estrus while still at high metabolic risk.

Because metabolism and reproduction are tightly linked, hybrid digital twins that track both domains simultaneously are particularly promising. Mechanistic energy-balance models can be driven by observed intake proxies and milk output to estimate body-reserve dynamics, while statistical models estimate probabilities of estrus expression, conception and early embryonic loss. The twin can simulate alternative management strategies, such as delaying insemination, modifying body-condition targets or adjusting transition rations, and project their impacts on milk yield, calving interval and culling risk.

4.3. Precision Nutrition and Feed Efficiency

Feed is the largest variable cost in dairy farming and a major contributor to environmental impact, making precision nutrition a central application of digital twins. Conventional rations are formulated at the herd level despite substantial variation in intake capacity, production potential and health status among cows. Mechanistic nutrition models such as the Cornell Net Carbohydrate and Protein System and the NASEM nutrient-requirement models link nutrient intake to milk yield, body reserves and maintenance, providing a foundation for individualized nutritional simulation [36]. When parameterized with cow-specific data, including body weight, parity, days in milk and milk composition, and updated continuously with intake and behavioural proxies, these models enable a twin to estimate each cow's current and predicted energy balance.

Dynamic concentrate-feeding systems are early implementations of individualized feeding. These systems calculate concentrate allowances in real time based on predicted energy requirements, observed milk yield and production targets. Improvements in feed efficiency and reductions in concentrate use have been reported when such systems are correctly configured, although outcomes vary with management context [36,37]. A digital twin extends this by simulating responses to dietary changes before implementation, for example, testing how increased starch, supplemental fat or methane-reducing additives might influence milk yield, body condition and rumen health over the next several weeks.

Digital twins also link nutritional strategies to greenhouse gas outcomes. By integrating intake, milk yield and manure-production predictions with emissions models, a twin can show how ration changes shift methane intensity per litre of milk. Pilot greenhouse gas tracking systems in several regions have demonstrated that feed-efficiency gains often provide simultaneous economic and environmental benefits, while more aggressive methane-suppression strategies require balancing production outcomes with metabolic stability.

4.4. Environmental Control and Emissions Management

Barn climate influences dairy cow welfare, health and productivity, especially under intensifying heat stress. Digital twins that link environmental sensor data such as temper-

ature, humidity, airspeed and solar load with behavioural and physiological indicators, including panting scores, lying time and intake patterns, can estimate heat-stress risk at both the cow and pen levels [38]. Such twins can simulate changes in ventilation settings, shade structures, cooling systems and stocking density to evaluate their effects on predicted body temperature and milk production.

Practical implementations often involve advanced climate-control algorithms that adjust fans, sprinklers and inlet openings based on both current conditions and predicted heat load. While many systems operate at a barn level, digital twins extend this by modelling heterogeneous responses among cows and identifying individuals that remain at risk even when overall barn conditions appear acceptable. This animal-centred view supports targeted interventions such as moving susceptible cows to cooler pens or adjusting ration energy density during heat waves.

Environmental digital twins can also be coupled with greenhouse gas accounting. Integrating predicted manure output from nutritional twins with storage-temperature profiles and handling schedules enables estimation of methane and nitrous oxide emissions under alternative manure-management strategies. A recent greenhouse gas tracking concept for dairy farms combines these elements into a unified platform that estimates current emissions and evaluates the mitigation potential of interventions such as diet reformulation, manure cooling or anaerobic digestion. Although still at the prototype stage, such twins illustrate how environmental and nutritional components can be merged to support productivity, welfare and climate objectives.

Table 1. Representative near-digital-twin and digital-twin-inspired systems relevant to dairy and poultry.

Species	System/Study	Core Sensors and Data Sources	Model/Analytics Approach	Maturity (Concept/Prototype/ Twin-Inspired)	Reported Capabilities (Not Full Twins)	Evidence Type
Dairy	On-farm data integration platform [39]	Milking robot data (yield, conductivity, flow), activity and rumination sensors, barn climate (temperature, humidity, gases)	Hybrid mechanistic and data-driven analytics for production, health, climate	Twin-inspired system; no continuous bidirectional coupling	Demonstrated integration of heterogeneous real-time streams into a unified herd/barn dashboard; illustrative health and environmental monitoring use cases [39]	Field case studies
Dairy	Mastitis risk-prediction ML systems [30]	Milk yield, conductivity, milking interval, activity, rumination, parity, days in milk	Supervised ML classification models	Decision-support tool; not a twin	Sensitivity above 80–90 percent and specificity around 70–85 percent for mastitis detection versus clinical diagnosis or SCC thresholds [30]	Retrospective and prospective evaluations
Dairy	Rumen-bolus health monitoring prototypes [22,32]	Rumen boluses (temperature, pH), accelerometry, milk-yield data, climate sensors	Time-series analytics and probabilistic health-state estimation	Prototype physiological-monitoring systems; not twins	Early warning of fever, acidosis and intake disruption; proof of life-long in-animal sensing [22,32]	Pilot deployments
Dairy	Precision feeding and nutrition decision-support tools (Bach; CERC GHG concepts) [34–36]	Milk yield, components, body weight, BCS, feeding-station logs, ration composition, manure output	Mechanistic nutrition and energy-balance models with scenario simulation	Simulation and decision-support systems; not twins	Improved concentrate allocation in some herds; ability to test nutritional and methane-mitigation strategies in silico [34–36]	Field experiments and simulations
Poultry	Broiler FCR optimization [40–45]	House climate (temperature, humidity, ventilation), stocking density, feed and water use, management actions	LSTM predictive model plus genetic-algorithm planner	Twin-inspired optimization system; partial closed-loop	Improved feed conversion ratio in limited commercial pilots; multi-house adaptive planning [44,45]	Field trials

Table 1. *Cont.*

Species	System/Study	Core Sensors and Data Sources	Model/Analytics Approach	Maturity (Concept/Prototype/ Twin-Inspired)	Reported Capabilities (Not Full Twins)	Evidence Type
Poultry	IoT/ML welfare-monitoring framework [40]	Environmental sensors (temperature, humidity, ammonia, CO_2, light), cameras, microphones	Modular IoT/ML architecture linking environment, behaviour and welfare	Conceptual framework; not a twin	Illustrates how multimodal sensing and analytics could feed a virtual welfare model [40]	Concept + small prototypes
Poultry	Production-system twin concept [41]	House-climate sensors, feed/water meters, production and logistics records; optional vision/audio	System-of-systems architecture covering health, nutrition, environment and economics	Conceptual digital-twin vision	Roadmap for flock-level integration across the production cycle [41]	Framework descriptions
Poultry	IoT house-environment platform [38]	Distributed temperature, humidity and gas sensors; feed/water meters; optional cameras	Cloud-based analytics and rule-based control	Infrastructure for potential twin development; not a twin	Real-time climate monitoring and automated control; foundation for future twin integration [38]	Field deployment

5. Poultry Applications

5.1. Poultry Digital-Twin Frameworks

Poultry digital-twin concepts have emerged at the intersection of Internet of Things architectures, machine learning and welfare-oriented monitoring systems. Ojo and co-authors reviewed Internet of Things and machine learning techniques for poultry health and welfare and proposed a modular architecture in which sensor networks feed analytics layers for environment, behaviour, health and welfare, topped by a digital-twin module that supports real-time simulation and decision support [40]. In this design, the twin is a virtual representation of the poultry house and flock that takes in environmental variables such as temperature, humidity, ammonia and carbon dioxide, together with behavioural features including activity and vocalization, in order to model dynamic states of flock health and welfare [40]. A recent review on digital twins in poultry farming similarly defines a virtual replica of the house and flock driven by Internet of Things data and artificial intelligence models, and highlights conceptual and pilot implementations where virtual simulations are used to test environmental and feeding strategies before they are applied in the barn [41]. Related work on digital-twin-enabled automation systems for poultry environments further illustrates how sensing, analytics and actuation can be orchestrated into integrated control platforms [42]. Broader overviews of digital twins in precision livestock farming provide additional context and underscore the relevance of these concepts for poultry production [43].

Not all smart poultry systems qualify as genuine digital twins, and it is important to distinguish rich monitoring from fully coupled twins. Systems that only collect sensor data and present dashboards, even when they employ machine learning-based anomaly detection, remain advanced monitoring platforms because the virtual representation neither drives control decisions nor simulates counterfactual scenarios in a closed loop [41,46]. Frameworks that move closer to twin behaviour incorporate bidirectional coupling: environmental and behavioural data continuously update a virtual model, which in turn generates recommended or automatically applied actions such as adjusting set-points, modifying feeding regimes or triggering biosecurity procedures [40–42]. The most twin-like poultry systems therefore combine multimodal sensing of the house and flock, explicit modelling of dynamics such as growth, welfare, disease risk and the climate and the ability to test and apply management actions through the same platform [41,46].

5.2. FCR and Growth Modelling

Feed conversion ratio and growth trajectories are central performance indicators in broiler production and natural targets for digital twin models. Klotz and colleagues developed one of the most detailed twin-like control systems for commercial broiler houses by combining long short-term memory neural networks with a genetic algorithm to generate adaptive action plans [44]. Their model received time-series inputs describing house climate, stocking variables and management decisions and predicted future outcomes such as the feed conversion ratio, mortality and thermal comfort for each house in an interconnected network [44,45]. On top of this predictive model, a genetic algorithm searched over candidate daily action plans, for example, sequences of temperature and ventilation set-points, to identify options predicted to yield improved performance while respecting operational and welfare constraints [44]. The system was deployed across multiple smart poultry houses, with optimized plans propagated through a supervisory network so that strategies performing well in one house could inform control in others [44,45].

Field experiments with this long short-term memory plus genetic-algorithm systems showed measurable improvements in the feed conversion ratio relative to specialist-configured conventional plans, although results were reported for a limited number of flocks and under specific climatic conditions [44]. The architecture satisfies key digital-twin criteria because it maintains a dynamic data-driven virtual model of each house, uses that model to simulate alternative management actions and closes the loop by implementing selected plans in the physical system. This contrasts with many growth and climate-control studies that remain in the simulation domain, in which mechanistic or data-driven models of broiler growth and barn climate are evaluated entirely in silico and are not tightly integrated with real-time sensor data or on-farm control hardware [41,46]. Such simulation-only work offers insight into potential strategies but, without continuous synchronization with real houses and feedback of actions, does not constitute a full digital twin.

Beyond the Klotz framework, other studies have explored predictive analytics for broiler feed conversion using Internet of Things and machine learning approaches, often focusing on relationships between environmental variables, stocking densities, management practices and final performance [46,47]. These models can inform decision making but are typically run offline and updated only when new data batches are analyzed. Integrating them into a twin would require continuous learning from live sensor streams and embedding them within a control loop that suggests or applies daily adjustments to set-points, lighting or feeding programmes. Current evidence suggests that, to date, the multi-house long short-term memory plus genetic-algorithm system remains one of the few published examples where feed conversion optimization is both model-based and field-validated within an explicitly twin-like architecture [44,45].

5.3. Health, Welfare and Biosecurity Digital Twins

Health and welfare are the primary focus of the Internet of Things and machine learning framework proposed by Ojo and colleagues, which explicitly includes a digital-twin module that couples environmental and behavioural data streams [40]. In this architecture, sensors capture temperature, humidity, ammonia, carbon dioxide, lighting and noise levels, while cameras and microphones provide information on flock distribution, movement and vocalization [40,47]. These data feed into machine learning models that classify welfare states, for example, normal, heat-stressed or fear-related agitation, and that detect early signs of respiratory disease or distress. The resulting states then update the virtual poultry house. The digital-twin module is envisaged as running what-if simulations, such as lowering stocking density or intensifying ventilation, and providing recommendations to improve welfare and reduce disease risk before problems escalate [40,41].

A recent framework paper on digital twins in poultry production extends this concept to a full production-system twin, including modules for health, nutrition, environment, logistics and economics [41]. The authors propose that a comprehensive twin should cover the entire broiler or layer cycle, from hatching through brooding and grow-out to slaughter or end of laying, with virtual representations of batches, houses and processing stages [41]. Within this structure, biosecurity is represented as a spatial and temporal risk model that responds to bird movements, staff traffic and environmental contamination indicators, enabling the twin to flag high-risk areas and suggest targeted disinfection or movement restrictions [41,46].

There is also a growing body of work on predictive analytics for disease prevention that aligns closely with twin principles even when the terminology is not used explicitly. These systems use high-frequency sensor data and historical records to model the probability of respiratory or enteric disease outbreaks and to identify leading indicators in climate, feed and behaviour patterns [46,47]. When connected to real-time dashboards and alert systems, they provide early warnings that can trigger targeted vaccination, treatment or culling, thereby tightening the integration between sensing, modelling and biosecurity action in a manner that is functionally twin-like, even if a fully elaborated virtual replica is not described [40,46].

5.4. Environmental and Welfare Monitoring

Poultry production lends itself to virtual sensing approaches in which computer vision and audio analytics infer welfare and environmental states that are difficult or costly to measure directly. Jia and colleagues developed an intelligent service platform for poultry houses that uses distributed Internet of Things sensors for climate and resource use, combined with cloud-based analytics and mobile interfaces for managers [48]. Their system provides real-time visualization of temperature, humidity, gas concentrations, water and feed consumption and can be extended with cameras to derive behaviour indices such as flock dispersion and activity [48]. Although primarily a monitoring and control platform, it contains core building blocks for a digital twin, including structured data pipelines, cloud analytics and the potential to layer predictive models on top of sensor streams.

At the brooding stage, fuzzy-logic controllers have been proposed for heating and ventilation to maintain optimal comfort under uncertain conditions. Adek and co-authors, for instance, designed a fuzzy brooder controller that adjusts heating power based on temperature and humidity inputs, achieving more stable thermal conditions and improved chick performance compared with simple on-off thermostats [49]. Integrating such controllers into a twin would involve treating the fuzzy rules as part of the control layer of a virtual brooder, updated by real-time sensor data and calibrated with observed chick behaviour and growth, so that deviations between predicted and observed states trigger adaptation of rule parameters.

Vocalization and behaviour recognition pipelines represent another frontier where digital twins and advanced perception intersect. A recent review on advanced detection technologies in poultry summarizes how deep learning-based computer vision models can recognize postures such as sitting, standing and wing flapping, as well as locomotion patterns and individual behaviours at a flock scale, while audio models detect coughing, sneezing or stress calls amid barn noise [50]. When fused with environmental data, these perception systems can infer latent welfare states such as fearfulness, thermal discomfort or respiratory distress and feed them into a virtual representation of the flock [47,50]. Experimental multi-sensor artificial intelligence platforms show that combining cameras, microphones and environmental sensors allows for earlier detection of anomalies than any single modality, which is a key requirement for robust health- and welfare-oriented twins [46,50].

Some prototype systems go further by explicitly creating a digital twin and reinforcement-learning control loop. One study describes a digital-twin- and Internet of Things-enabled reinforcement-learning system that learns optimal environmental-control policies by interacting with a virtual replica of the poultry house, then deploys these policies in the real house to reduce manual intervention and improve health outcomes [51]. In this design, the twin serves both as a predictive model and as a safe testbed for new strategies, while the reinforcement-learning agent closes the loop between simulation and practice [51]. Such architectures exemplify how virtual sensing, decision algorithms and control hardware can be orchestrated into genuinely twin-like systems that act continuously on behalf of farmers to maintain welfare and productivity.

5.5. Comparative Synthesis of Dairy and Poultry Twins

While both dairy and poultry sectors are moving toward digital-twin adoption, their trajectories are shaped by distinct biological and economic constraints. Dairy systems prioritize the individual animal due to high unit value and long productive life, driving the development of sophisticated on-animal wearables and metabolic models. In contrast, poultry systems focus on flock-level optimization due to low individual margins and rapid turnover, relying heavily on environmental sensing and computer vision (Figure 2). These fundamental differences dictate divergent technical architectures, validation challenges and control goals, as summarized in Table 2.

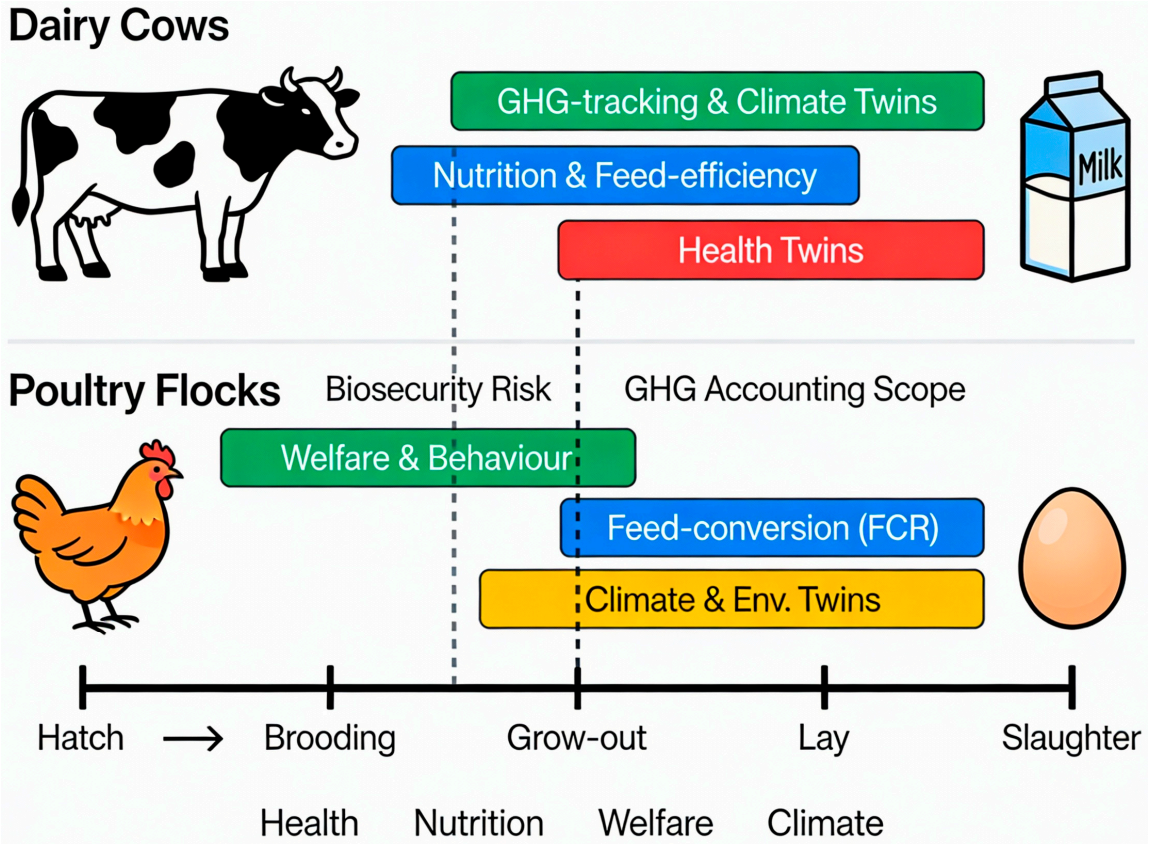


Figure 2. Life-cycle applicability of digital-twin modules for dairy cattle and poultry. Dairy twins (**top**) operate continuously across the lactation cycle, focusing on health, nutrition and emissions. Poultry twins (**bottom**) follow the flock timeline from hatch to slaughter/end of laying. Vertical dotted lines indicate asynchronous data integration for biosecurity risk (early-stage prevention) and GHG accounting (life-cycle assessment), which span multiple production phases.

Table 2. Comparative analysis of digital-twin architectures for dairy and poultry systems.

Feature	Dairy Cattle (Individual Focus)	Poultry (Flock Focus)
Primary Unit	Individual animal (high economic value)	Flock/house (low individual value)
Sensing Strategy	On-animal wearables (collars, boluses), in-line milk sensors	Environmental sensors, cameras, microphones (non-contact)
Dominant Models	Mechanistic (metabolic, reproductive physiology)	Statistical/machine learning (growth curves, computer vision)
Control Goals	Individual health, estrus detection, precision feeding	Climate control, disease spread, aggregate feed efficiency
Validation Challenge	Long physiological cycles (lactation), complex individual variability	Short cycles (broilers), difficulty tracking individuals in mass
Adoption Driver	Labour saving (estrus/health), individual yield optimization	Cost reduction (feed/energy), mass welfare assurance

6. Cross-Cutting Themes

6.1. Climate and Carbon Accounting

Digital twins for livestock are frequently promoted as tools for climate-smart agriculture, yet the carbon footprint of the digital infrastructure itself has only recently been quantified. La Rocca and colleagues developed a bottom-up method to estimate the carbon footprint of digital agriculture scenarios by accounting for the embodied and use-phase emissions of sensors, gateways, servers and communication networks across different farm sizes [52]. Their analysis shows that digital agriculture encompasses a heterogeneous portfolio of devices with widely varying footprints, and that more complex, compute-intensive devices do not always deliver proportional performance gains that would compensate for their higher emissions [52]. Follow-up methodological work extends this approach into a broader framework for adapting life-cycle assessment methods to smart-farming technologies, arguing for multi-indicator assessments that consider not only greenhouse gases but also resource use, such as metals and water, associated with ICT infrastructures [53].

These device-level assessments align with the growing critical literature on the environmental footprint of agritech. A 2024 analytical report argues that digital tools are often framed as unambiguously green levers for decarbonizing agriculture, while the emissions and resource demands of the tools themselves remain a blind spot in policy and industry narratives [54]. The report synthesizes emerging work on the digital sector's rapidly growing share of global greenhouse gas emissions and warns that large-scale deployment of sensors, cloud services and data-driven platforms in agriculture could lock farms into high-energy trajectories if the carbon costs of digitalization are not explicitly managed [54]. It calls for more careful trade-off analyses between conventional practice improvements and digital optimization, and for governance frameworks that reserve digital deployments for problems where they clearly outperform lower-tech alternatives on a full-system basis [54].

Against this backdrop, livestock digital-twins occupy an ambiguous position. On one hand, they can integrate sensor data with mechanistic and statistical models to identify low-emission feeding strategies, optimize barn climate control and reduce avoidable losses, lowering emissions per unit of milk or meat. On the other hand, twins depend on always-on sensing, edge computing and often cloud-based analytics, which incur their own energy and material costs. Existing life-cycle assessment work in digital agriculture has focused on generic smart-farming deployments in cropping systems or mixed farm scenarios rather than on livestock-specific digital twins [52,53]. As of 2025, there are still no published life-cycle assessments that quantify the cradle-to-grave environmental impacts of a complete livestock digital twin stack, from sensors and communication networks to servers and

model training, nor studies that compare those impacts against measured mitigation benefits in real dairy or poultry farms [52–54].

This evidence gap has practical consequences. Without robust life-cycle assessments, it is impossible to know whether a given digital-twin deployment delivers net climate benefits once hardware turnover, data-centre energy use and network traffic are considered [52–54]. Carbon-accounting twins that simulate enteric methane, manure emissions and energy use at the farm scale may risk double counting if they ignore the emissions of the digital layer that enables their calculations. Future research directions include integrating device-level emission factors into farm-scale twin architectures so that digital infrastructure is treated as part of the production system rather than as an externality, benchmarking different sensing and computing configurations, for example, camera-heavy versus sparse-sensor designs, on a joint axis of mitigation potential and digital footprint, and exploring Green AI approaches that reduce model complexity and communication overhead while preserving sufficient accuracy for decision support [52–54]. Such work would allow livestock digital twins to move from assumed climate solutions to demonstrably climate-beneficial interventions.

6.2. Security, Privacy and Cyber-Physical Risk

As dairy and poultry operations adopt networked sensors, cloud platforms and automated control systems, digital twins also introduce a new layer of cyber-physical vulnerability. The 2025 review "Safeguarding Digital Livestock Farming" provides a comprehensive synthesis of the cyber threat landscape confronting digitalized dairy and poultry farms [55]. It documents incidents and plausible scenarios in which ransomware, hacktivist interference or state-sponsored intrusions compromise milking robots, feeding systems or climate-control equipment, with cascading effects on animal welfare, productivity and food safety [55]. Because livestock digital twins sit at the intersection of data collection, analytics and actuation, an attack on data integrity or control outputs can translate rapidly into real-world harm, such as feed withholding, thermal stress or disrupted milking routines [55].

Building on this risk analysis, the same work proposes a multilayered cybersecurity roadmap tailored to digital livestock farming [55]. At the device and network layers, it recommends hardened Internet of Things devices, segmentation of operational technology networks from corporate IT, end-to-end encryption and strict authentication to reduce the attack surface of sensors, gateways and actuators [55]. At the data and analytics layers, it highlights the need for secure data pipelines, audit trails and anomaly detection that can flag suspicious patterns, such as implausible sensor readings or control commands, before they propagate through the twin and into physical actions [55]. At the organizational layer, it calls for regular security audits, incident-response planning and farmer-oriented training that recognizes social engineering and credential theft as critical weak points in otherwise sophisticated technical systems [55].

Cybersecurity concerns intersect with questions of privacy, data sovereignty and power asymmetries in digital agriculture more broadly. Analyses of agricultural digitalization and just transitions note that data from farms, including health, productivity and environmental indicators, are increasingly captured and processed by platforms controlled by technology providers, integrators and retailers rather than by farmers themselves [56]. This raises questions about who can access and monetize the high-granularity data generated by livestock digital twins, how those data might be used in contract negotiations or compliance monitoring and whether farmers can exit or switch providers without losing historical data that are essential for benchmarking [54,56]. Reports on agritech adoption suggest that fear of lock-in, lack of transparency about data use and unclear liability in the event of system failures contribute to farmer hesitation around highly integrated digital platforms [54,56].

Resilience of cyber-physical systems is another cross-cutting concern. Digital twins depend on continuous data streams and reliable connectivity to maintain synchronization with the physical farm, but many livestock operations contend with unstable rural broadband and harsh environmental conditions that degrade hardware [55]. A resilient design therefore requires graceful degradation: the twin should fall back to safe default behaviours or local control modes when data are incomplete or connectivity is lost, rather than attempting to extrapolate from corrupted inputs [55]. The cybersecurity roadmap for dairy and poultry systems explicitly advocates for redundancy in sensing and actuation, local override capabilities for farmers and veterinarians and routine drills to ensure that manual procedures can be restored quickly if digital systems fail or are temporarily taken offline during an incident [55].

Finally, data governance for livestock twins must address cross-border regulatory contexts and ethical questions about surveillance and autonomy. As regulations on environmental performance and animal welfare increasingly rely on digital records, farmers may feel compelled to adopt twin-like systems to access certain markets or certification schemes [56]. Ensuring that such transitions are fair will require clear rules on data ownership, portability and consent, as well as participatory processes in which farmers, workers and local communities help define acceptable uses of twin-derived data [54,56]. Security, privacy and resilience are therefore not peripheral technical considerations but central design constraints for livestock digital twins that aspire to be trustworthy, adoptable and compatible with just and sustainable agricultural transitions [55,56].

7. Evidence Gaps

Digital twins for dairy and poultry are advancing rapidly at the conceptual and prototype levels, yet the empirical evidence base remains narrow and uneven. Three gaps are particularly salient: the scarcity of robust field trials for key outcomes such as feed conversion, the near absence of systematic reporting on system failure and abandonment and the limited but revealing qualitative work on farmer perceptions and adoption barriers. Together, these gaps constrain movement from hype to verifiable evidence and limit the credibility of livestock twins as practical tools.

7.1. Limited Field Validation for Feed Conversion and Growth

Despite widespread claims that digital twins can improve feed efficiency, there is remarkably little field-validated evidence documenting feed conversion improvements in commercial poultry. The multi-house long short-term memory plus genetic-algorithm system developed by Klotz and colleagues remains the only peer-reviewed study reporting flock-level feed conversion gains from a twin-like control architecture under commercial conditions. Other Internet of Things and machine learning studies for broilers and layers focus on predicting growth or final performance from environmental and management variables, but these typically operate offline or remain in simulation without closing the loop through on-farm control. No additional field trials have demonstrated statistically robust, repeatable improvements in feed conversion attributable specifically to digital twins, leaving a pronounced gap between marketing narratives and documented performance.

In dairy systems, evidence for feed-efficiency or methane-intensity improvements attributable to digital twins is similarly sparse. Precision feeding and decision-support systems based on mechanistic models show that individualized concentrate allocation can improve efficiency in some contexts, but these studies usually predate explicit twin terminology and rely on simpler rule-based algorithms rather than continuously updated virtual cows. Recent greenhouse gas tracking concepts for dairy digital twins integrate ration, production and manure data into farm-level carbon dashboards, yet controlled trials

comparing emission trajectories under twin-supported and conventional management remain rare. The absence of longitudinal, controlled evaluations means that mitigation claims for dairy and poultry twins continue to rely primarily on extrapolation and simulation rather than replicated field evidence. The scarcity of field-validated FCR improvements suggests underlying structural barriers rather than simple technological immaturity. First, commercial confidentiality discourages the sharing of negative trial results, creating a publication bias where only successful optimization pilots are reported. Second, many 'digital twin' pilots suffer from integration latency; by the time a model processes batch-level weight and climate data to recommend a nutritional adjustment, the flock's growth trajectory may have already shifted, rendering the intervention reactive rather than predictive. Finally, the disconnect between engineering metrics (e.g., algorithm accuracy) and biological outcomes often leads to systems that are technically precise but biologically irrelevant for decision support.

7.2. Missing Data on Failure, Downtime and Abandonment

Reviews of precision livestock farming and digital agriculture repeatedly note that published studies rarely include detailed statistics on sensor failure rates, communication outages, data-loss percentages or system downtime. Our systematic screening confirms this gap: explicit reporting of quantitative reliability metrics (e.g., sensor drift rates, percentage of missing data, or system downtime duration) was present in less than 10% of the 104 included studies (Table S1). When technical issues are mentioned, they are typically described qualitatively, such as intermittent connectivity or occasional sensor malfunction, without quantifying frequency, duration or analytic impact. The cybersecurity roadmap for digital livestock farming explicitly remarks that systematic documentation of system failures, including non-malicious outages and user-driven discontinuation, is almost entirely absent from scientific literature.

For digital twins, which depend on continuous bidirectional coupling between physical and virtual systems, this lack of reliability data is especially problematic. While manufacturers rarely publish failure data, independent validation studies reveal significant reliability challenges in commercial environments. For example, a deployment of ZigBee-based environmental sensors in a commercial sow house reported a packet loss rate of 4% and a 6.5% outlier rate for CO_2 sensors even after preprocessing. Similarly, field evaluations of ammonia sensors indicate that high-humidity, dust-laden barn environments can degrade sensor sensitivity within 12–24 months, significantly shorter than the 3–5 year lifespans often cited in technical specifications. These hardware vulnerabilities are compounded by connectivity gaps; however, the emergence of edge computing architectures (Section 3.2) offers a partial solution by processing critical alerts locally, thereby reducing reliance on unstable cloud uplinks. Without such transparent reporting on how often sensors drop out or models require re-initialization, it is impossible to assess operational robustness in commercial barns.

7.3. Under-Explored Farmer Perspectives and Social Dimensions

The social science literature on livestock digitalization lagged behind technical developments for many years, but recent studies provide insight into how farmers perceive and negotiate with precision technologies. Interviews and focus groups with European dairy farmers adopting or considering precision livestock systems highlight concerns about data ownership, lock-in, workload and trust in algorithmic recommendations [57]. Some farmers report that technologies marketed as labour-saving instead increase cognitive burden by generating more alarms and dashboards to monitor, while others fear that sensor-based

scoring of welfare or environmental performance may be used by processors or retailers to impose compliance demands without commensurate price premiums.

Reviews of precision poultry farming adoption indicate a similar gap between integrator enthusiasm for data-rich monitoring and growers' reservations about autonomy, opaque decision rules and unclear value propositions [57]. Studies in the United Kingdom and Europe show that growers view digital tools as potentially useful but emphasize that adoption requires demonstrable reductions in stress, workload or risk, along with clear procedures for assigning responsibility when automated recommendations conflict with farmer judgement. Very few digital-twin projects have incorporated participatory design or co-created evaluation metrics with farmers, veterinarians or workers, raising the risk that new twin systems will reproduce the same adoption barriers encountered in earlier waves of precision livestock technologies.

8. Adoption Barriers and Comparative Challenges

While evidence gaps reveal what is unknown, the available literature points to recurring barriers that shape adoption trajectories. These barriers differ in intensity and form between dairy and poultry due to structural, economic and governance differences within their respective value chains. Table 3 summarizes key themes emerging across empirical studies and sector reviews.

Table 3. Key adoption barriers for dairy versus poultry digital twins.

Barrier Category	Dairy Digital Twins	Poultry Digital Twins	Likely Direction of Effect
Connectivity	Patchy rural broadband; individual farms responsible for upgrades	Often better at complex level, but multi-house data loads strain bandwidth	Slightly higher barrier in dairy
Capital expenditure	High per-cow sensor and robot investment; long payback horizons	High infrastructure cost across many houses; often borne jointly with integrator	Similar magnitude, differing control
Labour skills	Time and IT-literacy constraints on family farms	Reliance on integrator analytics; limited local capacity	Comparable, with centralization in poultry
Integration	Fragmented value chains	Highly integrated; data control concentrated upstream	Greater structural dependency in poultry
Perceived value	Workload increase without clear ROI undermines trust	Growers skeptical of surveillance or unilateral benchmarking	Trust challenges in both sectors
Regulation and retailers	Rising reporting requirements	More acute and prescriptive in poultry	Higher immediate barrier in poultry

8.1. Structural and Economic Barriers

Connectivity remains a foundational constraint for both sectors. Many dairy farms operate in areas with unreliable broadband or cellular coverage, complicating cloud-based analytics and remote support for digital twins. Poultry integrators often invest in higher-quality connectivity across complexes, yet multi-house farms may still experience bottlenecks that limit real-time video or audio processing, especially in lower-margin regions. Capital expenditure requirements also differ individual-cow sensing and milking-robot integration create high upfront costs in dairy, while high-density camera and environmental sensor arrays across multiple broiler or layer houses generate considerable investment at flock scale. In both sectors, farmers weigh these costs against volatile margins and uncertain returns, and independent return-on-investment assessments remain rare [58].

Labour skills and organizational capacity represent another barrier. Operating and maintaining digital twins requires IT literacy, familiarity with dashboards and the ability to interpret algorithmic outputs, which may be limited on family-run dairy farms and contract poultry operations. Adoption studies note that even when hardware functions correctly, lack of time or training to interpret data leads to underuse or abandonment [57–59]. Poultry

integrators sometimes provide centralized analytics and deliver recommendations directly to growers, but this can heighten perceptions of top-down control and reduce opportunities for local adaptation of twin-based insights.

8.2. Governance, Power and Perceived Value

Integration with processors and integrators is both an enabler and a barrier. In contract poultry systems, integrators often purchase and operate digital systems, which accelerates deployment but concentrates control and data flows away from growers. Growers express concern that detailed metrics derived from twins could be used to adjust settlement formulas or impose penalties without transparent recourse [57]. In dairy supply chains, processors and retailers increasingly require environmental and welfare reporting and may view digital twins as verification tools, yet farmers remain wary of one-sided data access and unclear value beyond compliance.

Perceived value therefore depends not only on technical performance but on how benefits and risks are distributed along the value chain. Studies of agritech adoption identify unclear value propositions and fear of dependency on vendors as common reasons for slow uptake of advanced systems [58]. Farmers repeatedly state that technologies must reduce labour, stress or risk or measurably improve productivity or welfare. Digital twins, being more abstract and integrated than single-purpose sensors, may encounter an even higher evidentiary bar for perceived usefulness.

8.3. Regulatory and Retailer Pressure

Regulatory and retail pressure is emerging as both a driver and a barrier. In regions with tightening climate targets and strengthening welfare standards, supply chains seek more granular and auditable data on farm practices. Digital twins can, in principle, generate the continuous records needed for carbon reporting, welfare certification or antimicrobial-use tracking. Some retailers are beginning to pilot digital audit schemes in collaboration with technology providers [58]. However, farmers fear that such requirements may become de facto prerequisites for market access, locking them into specific platforms and data-sharing arrangements. This concern is acute in poultry, where grower bargaining power is limited relative to integrators and retailers.

Regulators have yet to develop frameworks for evaluating and certifying complex algorithm-driven systems that influence animal management. The cybersecurity roadmap for digital livestock farming argues that certification should include resilience, security and data-governance attributes rather than solely functional performance [55]. Without such guidance, farmers may rely heavily on vendor claims, heightening uncertainty during adoption decisions.

9. Future Directions: Reference Farms and Green AI

Digital twins for dairy and poultry now face a pivotal moment, as the next decade must shift from proofs of concept toward independently evaluated, energy-efficient systems that demonstrably earn their carbon and welfare claims. Two strategic directions stand out: establishing multi-site reference farms for rigorous evaluation and embedding Green AI principles into perception and modelling so that twins are effective and computationally frugal [52,55,60–65].

9.1. Reference Farms for Hard Evidence

A coordinated network of reference farms would provide the empirical backbone that livestock digital twins currently lack. These farms would function as living laboratories that host complete twin stacks from sensors and edge devices through models and control algorithms, operated over at least 24 months to capture seasonal variation and management

changes. In dairy, a realistic configuration could include eight to ten farms per region, stratified by herd size, housing type and milking technology, with 200 to 400 cows per farm contributing data through milking systems, behaviour sensors and environmental monitors. In poultry, 20 to 30 houses across several complexes, spanning distinct climates and genetic lines, could host climate, welfare and feed-conversion twins across a minimum of six flock cycles per house, providing adequate statistical power for flock-level outcomes.

These reference farms would collect harmonized metrics covering production, including milk yield, feed conversion, growth and mortality; health and welfare, including clinical events, behaviour-based scores and injury indicators; environmental performance, including enteric and manure emissions and energy use; economics, including capital and operating costs and labour use; and digital-system performance, including uptime, sensor-failure rates, latency, model error and the energy consumption of edge and cloud components. This evidence base would enable robust comparisons between periods or units with and without twin support, using quasi-experimental or causal-inference designs rather than simple before–after anecdotes.

Reference farms also create a platform to institutionalize the Green AI arithmetic proposed for agricultural AI. This approach argues that systems should demonstrate that emissions avoided on farm exceed emissions generated by model training, inference and hardware manufacture and disposal [60–64]. By logging the energy use of perception models, communication networks and servers, and combining this with farm-level mitigation data, reference farms can quantify whether a given twin is climate-beneficial, climate-neutral or climate-negative over a defined timeframe. This would operationalize recent proposals for standardized reporting of AI energy and carbon metrics in livestock systems, including transparent disclosure of training energy, inference energy, hardware lifetimes and embodied emissions [60–64].

To be credible and widely accepted, reference farms should be governed through partnerships between farmers, researchers and technology providers rather than as proprietary testbeds. Work on sustainable computing for digital livestock and Green AI governance emphasizes the importance of open protocols, independent auditing and shared data-access arrangements that prevent lock-in and enable third-party re-analysis [55,60–64]. Embedding participatory impact-assessment methods, including interviews, focus groups and co-design workshops, would ensure that evaluations capture not only productivity and emissions but also labour burdens, autonomy, fairness and the distribution of benefits and risks along the value chain.

9.2. Green AI and Energy-Efficient Perception

The second opportunity lies in redesigning perception and modelling pipelines so that livestock digital twins respect planetary boundaries. Recent work on Green AI for livestock perception synthesizes efficient architectures, multimodal sensing strategies and deployment practices, arguing that energy use and carbon intensity must be treated as primary performance criteria rather than afterthoughts [60–64]. This research shows that many computer-vision and acoustic models used for lameness detection, body-weight estimation or poultry vocalization analysis are significantly over-parameterized relative to the complexity of barn environments, resulting in unnecessary compute and energy consumption during training and inference. Conceptual analyses of Green AI in livestock systems further show that cumulative emissions from training large models and running them continuously across farms can be substantial, and that without explicit constraints, digital livestock systems may drift beyond safe planetary boundaries while claiming mitigation benefits.

A concrete set of design levers is now available. Model-compression techniques such as pruning, low-precision quantization and knowledge distillation can reduce parameter counts and memory footprints by an order of magnitude, often with minimal loss of detection accuracy when guided by task-specific validation [60–64]. Lightweight architectures, including depthwise-separable convolutional networks and compact transformer variants, enable on-device inference on low-power edge hardware while still capturing salient visual and acoustic cues required for health and behaviour monitoring. Work on energy-efficient edge AI for environmental monitoring demonstrates that moving inference to the edge and transmitting only high-level events can significantly reduce communication energy and data-centre load, benefits that are directly transferable to barn contexts.

Hybrid cloud–edge strategies also offer promising gains. The Green AI arithmetic framework emphasizes that scheduling non-urgent analytics during periods of high renewable generation and running only time-critical inference locally can reduce total energy use by roughly one third and associated emissions by up to half, depending on electricity mix and workload [60–64]. Sustainable computing frameworks for digital livestock argue that architectural choices, including where models are trained, how often they are updated and which features are computed at the edge rather than in the cloud, should be explicitly optimized against both performance and carbon budgets. Reference farms create the ideal environment for benchmarking such configurations, comparing camera-heavy twins with sparse-sensor or audio-first designs on a joint axis of welfare gains and digital footprint.

Finally, recent proposals for a standardization roadmap for energy-efficient AI in livestock agriculture call for sector-wide metrics and reporting conventions. These include normalizing energy use to functional units such as kilowatt-hours per monitored cow-day or grams of carbon dioxide equivalent per million predictions, defining acceptable trade-off curves between model accuracy and energy use and encouraging shared, open models and datasets so that training emissions are amortized across many users rather than duplicated across proprietary implementations [60–65]. Coupled with governance principles from Green AI and sustainable computing, such standards would encourage vendors to compete not only on accuracy and features but also on energy and carbon performance.

In combination, reference farms and Green AI-aware design can move livestock digital twins from speculative promise toward verifiable, fair and climate-conscious practice. The central challenge is not only to build more intelligent models, but to ensure that their intelligence is demonstrably worth the environmental and social cost.

10. Conclusions

Digital twins for dairy and poultry are advancing rapidly in concept yet remain early in practice. Across species and production systems, the promise of continuously updated virtual counterparts that anticipate disease, optimize nutrition, fine-tune climate control and reduce emissions is compelling. However, the empirical foundation supporting these claims is still thin. Field-validated improvements in feed efficiency are limited to a small number of broiler trials, and no multi-year, multi-site evidence yet demonstrates that digital twins measurably improve milk yield, reduce methane intensity or stabilize welfare outcomes. Likewise, systematic reporting of failure rates, downtime and abandonment remains almost absent, leaving system robustness largely unknown. In many cases, the most optimistic narratives are sustained by simulation studies rather than by data from commercial barns.

At the same time, the digital infrastructures that animate twins carry material and energy costs that are rarely factored into assessments of climate benefit. Without transparent accounting of these costs, there is a risk that systems marketed as climate solutions may in practice shift energy burdens from barns to cloud platforms. The rise in Green AI highlights

that performance must be evaluated alongside carbon intensity and that lightweight, efficient architectures are essential if digital livestock technologies are to remain aligned with planetary boundaries.

Adoption dynamics further complicate the picture. Farmers across dairy and poultry systems emphasize that technologies must reduce labour, risk or cognitive load, yet many current prototypes increase the complexity of daily routines. Concerns about data rights, vendor lock-in and opaque decision pathways intersect with structural imbalances in value chains, particularly in poultry, where growers have limited leverage over data governance and platform access. Trust, transparency and independent evaluation are therefore as central to the future of livestock digital twins as any algorithmic advance.

The path forward is clear. Rigorous evidence requires reference farms that instrument full twin stacks and follow them through multiple cycles, documenting not only production and welfare effects but also system failures, energy use and carbon footprint. Green AI-aware design must guide the development of perception and modelling pipelines so that twins earn their environmental claims through measurable efficiency, not by offloading computation to external infrastructures. And governance frameworks must ensure that benefits and risks are distributed fairly across farmers, integrators and technology providers.

Digital twins will not transform livestock systems through technical novelty alone. Their value will depend on whether they can deliver sustained improvements in health, welfare, efficiency and environmental performance under real commercial conditions while respecting the constraints of farm labour, energy use and data sovereignty. The next decade will determine whether twins mature into credible, climate-aligned tools for dairy and poultry production or remain compelling prototypes awaiting evidence. The challenge is not merely to build smarter systems, but to build systems that are demonstrably worth their environmental, economic and social cost.

Ultimately, the transition from 'hype' to 'hard evidence' requires a fundamental shift in how digital twins are developed and evaluated. The pursuit of technological sophistication must be balanced with robust biological validation and a commitment to farmer-centric design. We call upon the research community to establish an interdisciplinary 'Digital Livestock Commons'—a shared framework for open data validation, failure reporting and standardization that places animal welfare and farmer well-being above proprietary opacity. Only through such radical transparency can digital twins evolve from promising concepts into the resilient, sustainable backbone of future livestock farming.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/agriculture16020166/s1, Table S1. Included Studies and Screening Outcomes (Structured Scoping Review Dataset). This table provides the full list of studies included in the scoping review following title, abstract and full-text screening. For each study, species focus, study type, validation level and reporting of quantitative performance or reliability metrics are documented. Table S2. Evidence Mapping of Digital-Twin Systems in Dairy and Poultry. This appendix summarizes the characteristics of digital-twin and digital-twin-inspired systems identified in the review, including sensing modalities, modelling approaches, validation context and reported outcomes. The table supports systematic comparison between dairy and poultry implementations.

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