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Nutritional Decision-Making in Smart Farms: Interaction between Animal Physiology and Algorithms

Article Info.

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Abstract

This study current aims to critically review the latest literature on integrating artificial intelligence and sensor technologies in the context of intelligent agriculture, particularly how models can support precision nutrition decision-making. The review of peer-reviewed articles with impact is based on 49 articles selected through systematic literature review criteria and analyzed to reveal general tendencies and methodological approaches. The findings identify the biosensors and computer vision systems as among the most promising sensor modalities for providing high-resolution temporal data streams. The software uses machine-learning and deep-learning techniques to convert such complicated datasets into predictive models that approximate the animal nutrient needs and physiological condition of a specific animal. In addition, a combination of these predictive algorithms and dynamic metabolic models offers a solid platform on which to produce a genuinely species-specific, such as cow- or pig-species-specific, feeding regime. The implementation of smart farm technologies advances precise animal nutrition, fostering synergistic relationships between advanced algorithms and animal physiology.

Keywords: Animal Nutrition, Smart farming, Metabolic Modeling

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Introduction

The growing population and changing dietary habits taking shape in developing countries are significant drivers of long-term growth in global consumption of animal protein, a trend likely to continue into the next decade. This growing demand puts a significant burden on the livestock industry, which has had to not only (1). Increase its production but also address serious issues related to resource efficiency, animal welfare, and environmental sustainability (2). Conventional, population-based feeding systems that rely on average nutritional requirements have become a major source of inefficiency because they cannot account for inter-individual differences in nutrient demands, enteral nutrient intake, and the efficiency of herd or flock metabolism. Accordingly, such systems often result in economic losses and poor animal health, and in the release of nitrogen and phosphorus, which also increase environmental pollution and greenhouse gas emissions.

To address these shortcomings, a paradigm shift has been initiated with the invention of Precision Animal Nutrition (PAN), which is currently a sub-discipline of the wider field of Precision Livestock Farming (PLF). The driving force behind this development is the need to make livestock systems more sustainable and efficient in resource use (3). The ability of PAN to adjust nutrition to meet the evolving needs of individual animals as they progress is a characteristic of PAN. It requires the integration of sophisticated data-driven solutions with biologically sound nutritional methods to achieve such granularity. The latest developments in big data analytics and artificial intelligence have provided new opportunities to identify specific animal nutrition, allowing the processing of large, complex data sets to outline the agro-ecosystem of the present day (4). In addition, the accelerated adoption of sensor technology has expanded our capacity to observe animal behavior, physiological health, and environmental conditions in real time, further enhancing our knowledge of adaptive physiology in the production process. The developments support the development of the big-data paradigm in agricultural research, where big and heterogeneous data are characterized by high velocities, necessitating new analytical paradigms to extract actionable information (5).

The final challenge is how to convert this heterogeneous, multifaceted information into viable nutritional choices, a key concern for smart farming systems. Therefore, machine learning and artificial intelligence frameworks have become inseparable in the context of precision livestock farming, as they enable the establishment of latent structures in multidimensional data and assist in predictive decision-making and forecasting that could not be achieved with traditional, human-oriented methodologies (6). Data-driven nutritional interventions can have a significant impact on metabolic status and production efficiency when used at the individual level, as demonstrated in dairy cattle. However, as long as they are combined with mechanistic models that accurately capture animal physiology and nutrient metabolism, the effectiveness of algorithm-based nutritional decision-making systems is possible. As demonstrated, when dcombined;ce methods and mechanistic models are combined, precision feeding systems used in animal production become more biological and more robust (7). Practical examples of these combined approaches are demonstrated in real-world practice, especially in precision pig feeding, which has shown how it can enhance feed efficiency and reduce environmental impacts, thereby improving the sustainability of intensive animal production systems (8).

Smart Livestock Farming Technological Foundations

The shift towards precision nutrition decision-making is supported by the invention and implementation of highly sophisticated data-acquiring technologies in the context of smart farming. These technologies are the heart of the Big Data ecosystem, which provides a stream of high-resolution data that is essential for effective farm management. The three major data streams received are animal-centric, feed-centric, and environment-centric (9). Internet of Things (IoT) offers a communication platform that connects the devices and sensors in a dissimilar manner, thus allowing real-time information transfer and aggregation (10).

In addition, the greatest importance is animal-centric sensors, which provide direct or indirect measurements of an animal's physiological state and behavior and are used in the nutritional decision-making process. These include wearable biosensors that can detect body temperature, heart rate, rumination time, and activity using accelerometers, and thus serve as indicators of metabolic stress, disease onset, and feed intake efficiency. Computer vision systems offer real-time, non-invasive determination of energy stores, eating behavior, body condition score (BCS), posture, and attendance at feed-bunks (11).

In-rumen measurements provide a direct measure of the digestive activity in the form of pH, temperature, and volatile fatty acid (VFA) concentration (12), whilst automated feeders and scales are required to estimate feed efficiency and nutrient demand in relation to nutrient intake, frequency of feeding, and body weight (BW). Feed-centric data are obtained from Near-Infrared Spectroscopy (NIRS) of feed mixers or on-farm laboratories, which offer non-destructive, rapid analysis of feed ingredients and total mixed ration (TMR) in relation to vital nutritional constituents (13). The four Vs of smart farming are generally defined by the four characteristics of big data: Volume, Velocity, Variety, and Veracity, as summarized in Table 1 (14). The most important sensor technologies used in these systems are given in Table 2.

Table 1: The 4 Vs of Big Data in Smart Farming (5, 14)

Dimension	Description	Example in Smart Farming
Volume	Large datasets are generated over time.	Terabytes of data per farm per year from continuous monitoring.
Velocity	Speed of data generation and processing.	Real-time sensor streams (milliseconds) for immediate feedback.
Variety	Diversity of data types and sources.	Structured sensor data, unstructured video/audio, and omics data.
Veracity	Accuracy and reliability of data.	Filtering sensor noise and communication errors via edge computing.

Table 2: Key Sensor Technologies for Precision Nutrition (10-13)

Sensor Category	Technology Examples	Measured Parameters
Animal-Centric	Wearables, Computer Vision, In-rumen sensors	Heart rate, BCS, Rumination time, pH, Temperature
Feed-Centric	NIRS (Near-Infrared Spectroscopy)	Nutrient composition of TMR, moisture, protein levels
Environment-Centric	IoT Weather stations, Gas sensors	Ambient temperature, Humidity, NH_3, CO_2 levels

The sheer amount of data, which may be in terabytes per farm per year, necessitates scalable data storage and processing systems. As a result, cloud-based systems that are more flexible and have higher computational capacity surpass on-premises servers. Velocity: The rate of data generation (e.g., in milliseconds with high-frequency sensors) requires real-time pipeline processing platforms such as Apache Kafka or Flink to support real-time decisions and avoid data bottlenecks (15). Variability, which includes not only structured sensor data but also less advanced unstructured video and audio data, requires highly sophisticated data-fusion algorithms that can provide a coherent, high-level view of animal health (16). Data credibility or veracity is yet another recurrent issue: sensor drift and communication errors, combined with environmental noise, may introduce significant inaccuracies that propagate through the decision chain. To address veracity issues, machine-learning-based anomaly detection models are frequently implemented at the edge so that unreliable files do not reach the core decision-support system, thereby maintaining the integrity of the entire data pipeline (17). The extensive use of these multi-source data would require complex sensor fusion algorithms that blend data from multiple sensors to produce a more consistent, accurate, and useful representation of the animal's state than any single sensor. To address the constraints of high data velocity and the requirements of real-time decision-making, there has been a growing inclination towards edge computing (18).

Edge computing reduces latency and bandwidth usage and makes systems resilient and robust to changes in the network infrastructure by performing initial processing, filtering, and even simple machine-learning model inference on local hardware. Such a decentralized paradigm is required when feedback is required instantly (e.g., lameness detection or a real-time feed-supplement adjustment) (19).

Mathematical models of nutrition decision making

Amidst the current technological innovations in exact livestock nutrition, the conversion of large data streams into practical dietary recommendations will be highly dependent on the complex algorithmic designs, most frequently, based on the fields of Artificial Intelligence (AI) and Machine Learning (ML) (20). Any attempt to transform large data streams into practical dietary guidelines will rely heavily on advanced algorithmic designs, most likely grounded in Artificial Intelligence (AI) and Machine Learning (ML). Intelligent farming systems rely on the extensive use of machine-learning algorithms to identify trends in multidimensional data generated by the system. Canonical methods, e.g., Decision Trees, random forests, support vector machines, are useful in classification and regression problems, e.g., classifying animal behaviour using accelerometer data or predicting milk production using physiological data (21). With Deep Learning, in particular Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), the boundaries of precision livestock farming have been expanded significantly (22). Convolutional networks are effective for visual data and provide extremely precise, non-invasive measurements of physical traits such as Body Condition Score. Repetitive architectures, and more so Long Short-Term Memory networks, are very amenable to time-series analysis, and thus they are better placed to predict nutrient requirements on a short-term basis (23). Various AI and machine learning algorithms and their primary applications in nutrition are presented in (Table 3).

Table 3: AI and Machine Learning Algorithms in PLF (6, 20-23)

Algorithm Type	Specific Technique	Primary Application in Nutrition
Supervised Learning	Random Forests, SVM	Behavior classification, Milk yield prediction
Deep Learning	CNN (Convolutional Neural Networks)	Automated Body Condition Scoring (BCS) via vision
Time-Series Analysis	LSTM (Long Short-Term Memory)	Short-term nutrient requirement forecasting
Optimization	Genetic Algorithms, PSO	Least-cost feed formulation under constraints
Advanced Paradigms	Federated Learning	Privacy-preserving global model development

Transfer Learning and progressive Deep Learning methods are being explored to overcome data sparsity by using pre-trained models on very large and generalized agricultural datasets and fine-tuning them for specific tasks (24). Federated Learning has likewise become well known as a privacy-preserving system that allows farms to combine to create a robust global model without exposing animal-sensitive and unprocessed data. Finally, these algorithms aim to provide a Decision Support System (DSS) that will deliver optimized, well-defined nutritional guidelines to farmers (25). These systems combine predictive models and farm-specific constraints, such as feed inventory, cost, and labor availability, to provide prescriptive results that not only give alerts but also deliver actionable intelligence.

A common problem with nutritional decision-making is that it is multi-objective, with the goals of maximizing production measures (e.g., milk yield, growth rate), improving health measures (e.g., reducing the risk of disease), and improving sustainability measures (e.g., minimizing nitrogen excretion), which can be in conflict (26). Genetic Algorithms and Particle Swarm Optimization are thus required to search large solution spaces and find reasonable compromises in the form of establishing the least-cost feed formulation that meets the predicted nutrient requirements without exceeding statutory limits on manure nitrogen (27). However, the complexity of these black-box models per se can be a barrier to adoption, underscoring the significance of Explainable Artificial Intelligence (XAI). XAI aims to explain why algorithms make decisions, which helps build trust between farmers and veterinarians, enables necessary action, and encourages human-AI collaboration.

Integration of animal physiology and metabolic modelling

Algorithms can be used to identify patterns with striking pattern-recognition and predictive capabilities, but their real value lies in the fact that their results are currently based on the underlying principles of biology (28). AI-focused integrations with dynamical metabolic modelling represent the future of accuracy in nutritional decision-making, bridging the gap between raw data and biological understanding (29). Conventional nutritional paradigms are usually fixed, based on average needs and relying on passive models. By contrast, mechanistic models describe the movement of nutrients through digestion, uptake, and distribution via physiological pathways as systems of differential equations that characterize metabolic rates (30).

The combination of AI and mechanistic modelling enables AI to parameterize and calibrate these models in real time for individual animals. As an example, an ML model could be used to simultaneously predict the physiological state of the animal by using real-time sensor measurements -rumination activity and pH of the rumen- and adjusting the parameters of a metabolic model to generate predictions (e.g., the projected glucose or amino-acid supply) which respond to the current physiological condition of the animal (31). This method can be further expanded to include complex physiological measurements and multi-omics. The large-scale profiling of small molecules (metabolomics) provides a direct indication of an animal's metabolic status (32).

Certain metabolite profiles in blood or milk have also been attributed to feed efficiency and metabolic disorders (33). Real-time acquisition of omics data in a farm environment is, however, both expensive and complicated. In turn, the current trend is to apply ML algorithms to build surrogate models that predict omics profiles or physiological states of interest from easily accessible sensor data (34). Such a hierarchical modelling scheme, in which sensor data feeds into an AI model that then utilizes a mechanistic metabolic model, has particular potential for truly individualized nutritional decision-making (35).

Digital Twin is at the peak of the integration of AI-metabolic models. A Digital Twin is a digital dynamic representation of an individual animal, continuously updated with sensor measurements and controlled in a mechanistic metabolic model (36). One of such twins can be used to test scenarios (what-ifs), e.g. when studying the physiological response of one animal to changes in the physical world as a result of changes in its feed formulation to reduce risk and improve the accuracy of nutritional intervention (37). In addition, the gut microbiome is now understood as a critical yet unstable component of animal physiology that determines the efficiency of nutrient utilization.

The second significant challenge is integrating microbiome data into the Digital Twin. In this case, the use of ML algorithms is necessary to identify microbial biomarkers that could guide adjustments to metabolic model parameters related to nutrient uptake and the production of volatile fatty acids (38).

Precision Feeding Systems and Sustainability Implications

The combination of the algorithmic approaches and in vitro metabolic modelling eventually led to the implementation of Precision Feeding Systems (PFS). These systems are designed to deliver the correct amount and formulation of feed to specific livestock, which improves feed conversion efficiency and prevents waste (39). Although the use of PFS is promising, there is considerable interspecific heterogeneity, as certain physiological states and management paradigms prevail in particular animal groups. The example of this representativeness can be seen in the context of dairy bovines, where the high economic value in monetary terms, as well as the intensive character of the production process, makes significant investments in accuracy technologies. The overarching goal is to balance energy and protein intake to match the bovine's changing lactational stage, milk production, and metabolic condition, all of which may change daily.

Moreover, algorithmic developments permit modulation of the Total Mixed Ration (TMR) with personalized top-dressings of single nutrients - bypass protein or insulated fats, and others. These systems consume real-time information on milk yield, weight changes, and rumination rate to predict the animal's energy balance, thereby enabling timely changes to the supplement (40). The findings of the empirical studies support the conclusion that individualized feeding programs are highly effective in boosting feed efficiency, reducing the incidence of costly metabolic diseases such as ketosis and acidosis, and ultimately increasing the cow's lifespan and productive life (41).

In swine production, where large herds of animals are kept, the main focus of precision feeding is to optimize the growth rates and, at the same time, minimize the excretion of nitrogen and phosphorus, which, in turn, are very problematic ecologically in the intensive pig production zones. The computer-vision cameras are used to non-invasively measure the pig's weight and size to provide the necessary data to sophisticated growth models, whereas the artificial intelligence algorithms apply the multi-stage feeding protocols, usually merging two or more diets in real-time in accordance with the specific needs of a particular sub-population or even a single pig (42). This practice has been shown to reduce excessive nutrient excretion, thereby significantly reducing the environmental impact of swine production and increasing profits through lower feed costs (27).

The strongest argument in favor of extensive use of precision nutritional decision-making is its enormous effect on the sustainability of livestock production. In essence, Precision Animal Nutrition (PAN) translates directly into improved feed efficiency. AI-based precision feeding systems have been shown to reduce nitrogen emissions by 10-30 per cent in dairy and swine enterprises, thereby providing an almost perfect balance between protein delivery and demand. It is this decrease in nitrogen excretion that, in turn, decreases the emissions of nitrous oxide (N_2O)- a strong greenhouse gas (43). Moreover, accurate nutritional treatment can reduce enteric methane (CH_4) emissions, which are one of the biggest sources of livestock industry climatic effects (44). With proper manipulation of feed-mix composition, either by maximizing the forage-to-concentrate ratio or by including certain additives, AI-based decision-support systems can direct ruminal microbiomes toward metabolic pathways that inhibit methane synthesis. To measure these advantages, Life-Cycle Assessment (LCA) is becoming part of the decision-making process, enabling the optimisation of feed formulation not only for cost and nutritional values but also for the project's carbon footprint and the eutrophication potential of the resulting ration (45). In the context of livestock production, it is impossible to appreciate the environmental dividends of PAN without directly linking it to economic viability, since feed costs are the highest variable cost. The precision feeding systems thus provide a high return on investment (ROI) by minimizing feed waste and maximizing feed-conversion efficiency (FCE) (46).

Difficulties and Future Projections

Although the opportunity for precision nutritional decision-making has the potential to transform, a few problems need to be addressed before effective, large-scale deployment is possible. The modern situation can be described as a diverse array of sensor technologies and data formats, creating a fragmented digital ecosystem that obstructs the creation of interoperable and scalable solutions. The answer to this involves concerted, immediate action by technology providers, researchers, and industry stakeholders to set an industry-wide standard for data collection, storage, and exchange (47).

Furthermore, the data required by accuracy systems demands an effective, scalable, and reliable cloud-based infrastructure capable of supporting the large volumes of data produced by modern farms. Creation of safe, decentralized data systems, which may be powered by blockchain technology, would help address the ownership and sharing conflict, allowing farmers to access their valuable data and share in the development of models. The more complex the AI models are, the less transparent they are, which restricts the trust and verification opportunities of farmers and veterinarians in the motivation behind the recommendations to them, which is a major obstacle to adoption. Therefore, the next research step must be to create explainable AI (XAI) systems specific to precision livestock farming that provide clear, understandable explanations of the reasoning behind all nutritional choices. The models should also tolerate sensor failures, noisy data and the rough and changing conditions of commercial farms, which should be tested outside the laboratory to on-farm performance measurements (48).

The role of AI and metabolic simulation is still in its early stages, despite small steps of progress. New models will need to embody the complex physiological interplay between the gut microbiome and nutrient absorption, the immunological role in nutrient partitioning during disease, and the complexity of interactions within the genetic environment. The growing use of high-resolution and continuous monitoring provokes deep ethical doubts about the privacy of animals and the opportunities for new surveillance and control. Such concerns must be resolved by definite ethical principles and standards grounded in considerations of animal welfare, focusing on indicators of positive emotional experiences and natural behaviour rather than efficiency and production. Also, it is important to provide equal access to the improved systems on both ends of the economic system to avoid the further technological divide between large corporate farms and small family-run businesses, which will lead to severe social and economic consequences in rural areas. The vision of smart farms in the long term is the implementation of embodied AI and autonomous robots, in the form of robotic feeders, which can distribute the relevant ration, follow up on responses, and design on-demand delivery in real-time and conduct minor health interventions, thus creating a real closed-loop animal management system (49).

Large language model (LLM) integration is becoming an efficient technology for synthesizing complex scientific literature and agricultural data into accessible interfaces, enabling farmers to interact with decision-support systems and promoting access to data-driven knowledge. However, the future of nutritional decision-making will go beyond algorithms; it will entail the creation of fully autonomous, biologically enlightened, and ethically responsible animal management that treats each animal as a living being and responds to the planet's exploding population, which will require sustainable food production (4).

Conclusion

A shift in the intelligent animal husbandry paradigm, with the implementation of individualized nutritional choice in intelligent farm systems, is the transition from population-based feeding models to individualized nutritional choice. The basis of this transformation lies in the combination of high-quality sensor technologies, rigorous artificial intelligence algorithms, and active metabolic modeling, all of which are key drivers of change. The benefits of precision feeding systems can be exemplified by higher feed efficiency, significantly lower environmental impact, and improved animal welfare. However, there are still some major issues, especially with data standardization, interoperability, and the interpretability of increasingly complex models. These issues need to be addressed to enable the creation of clear, ethically sound decision-support systems that can be easily applied to commercial operations.

Conflicts of interest

The authors declare that there is no conflict of interest.

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اتخاذ القرارات الغذائية في المزارع الذكية: التفاعل بين فسيولوجيا الحيوان والخوارزميات

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الخلاصة

تهدف هذه الدراسة إلى مراجعة نقدية لأحدث الدراسات المنشورة حول دمج الذكاء الاصطناعي وتقنيات الاستشعار في سياق الزراعة الذكية، لا سيما كيفية دعم النماذج لاتخاذ قرارات التغذية الدقيقة. تستند مراجعة المقالات المحكمة ذات التأثير إلى 49 مقالة تم اختيارها وفقًا لمعايير مراجعة منهجية للأدبيات، وخضعت للتحليل للكشف عن الاتجاهات العامة والأساليب المنهجية. تُشير النتائج إلى أن أجهزة الاستشعار الحيوية وأنظمة رؤية الحاسوب من بين أكثر تقنيات الاستشعار الواعدة لتوفير تدفقات بيانات زمنية عالية الدقة. يستخدم البرنامج تقنيات التعلم الآلي والتعلم العميق لتحويل مجموعات البيانات المعقدة هذه إلى نماذج تنبؤية تُقارب الاحتياجات الغذائية للحيوانات وحالتها الفسيولوجية. بالإضافة إلى ذلك، يوفر الجمع بين هذه الخوارزميات التنبؤية ونماذج التمثيل الغذائي الديناميكية منصة متينة لإنتاج نظام تغذية خاص بكل نوع، مثل نظام تغذية خاص بالأبقار أو الخنازير. يُسهم تطبيق تقنيات المزارع الذكية في تطوير التغذية الحيوانية الدقيقة، وتعزيز العلاقات التآزرية بين الخوارزميات المتقدمة وفسيولوجيا الحيوان.

الكلمات المفتاحية: التغذية الحيوانية، الزراعة الذكية، نمذجة التمثيل الغذائي.