



Artificial intelligence in large animal respiratory medicine: Current applications, clinical challenges, and future perspectives

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Abstract

Respiratory diseases represent significant causes of morbidity, decreased productivity, poor athletic performance, antimicrobial consumption, and economic losses in large livestock. Traditional diagnostics involve intermittent clinical examination, respiratory scoring, imaging, laboratory testing, and invasive sampling procedures that can overlook subclinical and transient manifestations of these diseases. AI, machine learning (ML), deep learning (DL), computer vision, bioacoustics, wearable monitoring, infrared thermography, and precision-livestock technologies create novel possibilities to assess health of lungs continuously and objectively. This review provides an overview of recent studies on the use of AI for detecting, monitoring, predicting and assessing clinically relevant respiratory diseases in large animals with a focus on cattle and horses. In cattle, the most advanced research on the application of AI deals with the detection and monitoring of bovine respiratory disease (BRD) using automated feeding systems, accelerometers, positioning technologies, cough monitoring, computer vision, thermal imaging, and multimodal ML. For horses, emerging applications include analysis of videos recorded by smartphones for diagnosing equine asthma, assisted upper-airway endoscopy with AI, analysis of breathing sounds via deep learning during exercise, and wearable and non-invasive respiratory monitoring. There is limited research related to buffalo, camel, sheep, and goat diseases using enabling technologies. In general, there is a shift from one-sensor classification towards multimodal, longitudinal, and individual respiratory phenotyping in all species. Barriers to progress in this area include small training datasets, varying definitions of the conditions under consideration, imbalanced classes, imperfect labels, lack of external validation, domain shift, missing sensor data, model calibration, explainability, high costs, and implementation into clinical practice. Therefore, AI should be considered as a technology of decision support and not as a replacement of expert opinion. Further efforts need to focus on multicenter datasets, consistent reference diagnoses, multimodal fusion, prospective external validation, explainability and uncertainty-aware models, federated and transfer learning, edge computing, and longitudinal individual predictions.

Keywords: artificial intelligence, respiratory disease, bovine respiratory disease, equine asthma, machine learning, computer vision, bioacoustics, wearable sensors, precision livestock farming, veterinary medicine

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Introduction

Respiratory disease represents an important health challenge in large-animal medicine because of its impact on welfare, productivity, growth, performance, and economics. In cattle, BRD still remains one of the most important multifactorial diseases and involves the interplay between infectious agents, host susceptibility, husbandry, transportation, nutrition, environment, and stress factors (Puig *et al.*, 2022; Kamel *et al.*, 2024). For horses, inflammatory lower airway disease, dynamic upper airway obstruction, infectious respiratory disorders, and exercise-induced respiratory dysfunction might lead to poor performance or intermittent manifestations (Couetil *et al.*, 2020; Lendl and Barton, 2024).

One of the key challenges in the assessment of the respiratory system in large animals is the episodic nature of the process. Clinical scoring systems are simple to apply yet depend on the examiner's expertise, the disease definition, and disease state. Additionally, there is no guarantee that clinical scoring will recognize all cases of pulmonary lesions (Decaris *et al.*, 2022). Lung ultrasound is a more accurate tool in calves' BRD diagnosis; however, it involves additional equipment and manipulation with the animal. In horses, history, clinical examination, endoscopy, bronchoalveolar lavage, respiratory function assessment, and exercise test are often needed to define the disease (Couetil *et al.*, 2020; Lendl and Barton, 2024).

However, physiological and behavioral abnormalities can precede clinical symptoms. For example, the development of BRD in calves leads to decreased milk intake, reduced activity, alterations in lying behavior, and changes in social/spatial behavior before clinical diagnosis (Cramer

et al., 2020; Bonafini *et al.*, 2024; Bushby *et al.*, 2024). This fact is the basis for the application of precision technologies as digital biomarkers. Automated milk feeding systems, accelerometers, positioning systems, microphones, thermal cameras, video recording, wearables, and environmental sensors provide longitudinal data that are processed using ML or DL algorithms. It is not the single value but the dynamics of variables from different biological domains.

Recent studies prove the feasibility of this approach. Bushby *et al.* (2024) used 229 features concerning feeding, movement, and social behavior of 172 calves and reported that the best model based on gradient boosting was able to achieve the accuracy of 77%, while movement features were most predictive (Bonafini *et al.*, 2024; Bushby *et al.*, 2024). Gomes *et al.* applied smartphone video for the analysis of nostril and abdominal movements and reported the accuracy of 89% for separating asthmatic from healthy horses in a small proof-of-concept population (Gomes *et al.*, 2026). Parmentier *et al.* proved the possibility of detection of expiratory events during high-intensity exercise in horses using temporal convolutional network with a median F1-score of 0.94 and respiratory rate estimation from noisy field recordings (Parmentier *et al.*, 2026).

However, the above studies illustrate another problem of artificial intelligence (AI): poor generalization. Many veterinary AI datasets are small-sized, single-center, imbalanced, and based on heterogeneous disease diagnoses. Thus, models might perform well in the development sample but lose their accuracy in other breeds, farms, climates, sensor systems, or disease prevalences. Hence, the clinical translation of the technology demands robust reference

diagnoses, animal- and farm-level validation, calibration, uncertainty estimation, explainability, and finally, the demonstration of how AI contributes to clinical decision making.

The aim of this review is the critical overview of AI in large-animal respiratory medicine with a focus on the technologies of highest clinical relevance, the evidence available for BRD and equine respiratory disease, the limited evidence for other large animal species, and the methodology required for clinically-reliable implementation.

In the present review, large animals is used to indicate cattle and horses, whereas buffaloes, camels, sheep, and goats are mentioned whenever there is evidence or any technology that can be used for evaluating their respiratory health.

Literature search and review approach

This review is intended to be a narrative critical appraisal of current and emerging uses of artificial intelligence (AI) in the respiratory medicine of large animals. The emphasis was on cattle and horses as these species were found to be the most studied for the purposes of disease-specific evidence, while other species like buffaloes, camels, sheep, and goats have been taken into account whenever the studies concerned respiratory monitoring technologies and AI-based approaches with potential for assessment of respiratory health. A literature search was performed using PubMed, Scopus, and Google Scholar databases combining various keywords relating to artificial intelligence, precision livestock technologies, and respiratory medicine. The keywords used were: *artificial intelligence, machine learning, deep learning, computer vision, bioacoustics, wearable sensors, precision livestock farming, respiratory disease, bovine respiratory disease, BRD, equine asthma, equine*

respiratory disease, respiratory rate, cough detection, infrared thermography, and upper-airway endoscopy. The search was performed until 17 August 2020. Peer-reviewed original research papers dealing with AI-, sensor-, or data-driven approaches for the detection, prediction, monitoring, or phenotyping of respiratory abnormalities have been prioritized for selection. Review articles have been used in order to create the necessary contextual and technological background and find additional primary literature sources. Papers covering non-respiratory applications have been selected when the technology used is a general-purpose platform with the potential for respiratory monitoring especially among species where no respiratory disease-specific AI evidence exists. The selected literature shows considerable heterogeneity regarding the species, population, definition of the disease, reference standard used for diagnosis, sensing modalities, AI techniques, validation approach, and performance measures. Thus, a meta-analytical approach was deemed inappropriate. However, a narrative critique can be applied giving priority to clinical significance, diagnostic ground truth, external validation, generalizability, multimodality, longitudinal nature, and the difference between disease-specific AI systems and enabling platforms.

Core artificial intelligence technologies for respiratory assessment

ML is the most popular technique in precision animal health. Supervised ML algorithms learn relationships between the predictor variables and target variable, e.g., healthy or BRD-status of the animals. Logistic and elastic-net regression, k-nearest neighbors, support vector machine, decision tree, random forest, gradient boosting, and neural networks have been used in livestock studies. Respiratory disease is especially

suitable for multivariable ML because of multiple concurrent dysfunctions such as feeding, activity, movement, temperature, social behavior, and respiration. Dynamics of a variable (moving average, lagged values, derivatives, or deviations from individual baseline) is often more informative than the absolute value (Bowen *et al.*, 2021; Cantor *et al.*, 2022; Bonafini *et al.*, 2024; Bushby *et al.*, 2024). DL is an extension of this approach that learns the representation of complex data, including images, video, audio, and high-frequency time series (Xiao *et al.*, 2025). Ghaffari *et al.* used deep convolutional neural networks and automated feeder data for disease detection in calves and showed that patterns of respiratory disease can be extracted from routinely generated behavioral data (Ghaffari *et al.*, 2022). For field respiratory monitoring, temporal architectures are especially relevant because respiratory signals are sequential. Parmentier *et al.* found that temporal convolutional network performed better than classical signal processing techniques for detection of expiratory events in exercising horses (Parmentier *et al.*, 2026). Computer vision provides the non-contact respiratory and behavior phenotype extraction from video. Possible outputs include respiratory rate, chest/abdomen excursions, nostril movement, posture, coughing-related movement, reduced locomotion, and respiratory effort. A typical pipeline includes animal detection, individual identification, anatomical region localization, feature extraction, and temporal analysis. Wu *et al.* (2023) combined YOLACT segmentation and CNN with bi-directional LSTM components to monitor respiratory behavior of multiple dairy cows and obtained the average accuracy of approximately 93.6% under different test conditions (Wu *et al.*, 2023). Shu *et al.* (2024) and Mantovani *et al.* (2024) provided the proof of concept of non-contact respiratory rate estimation in dairy cows using computer

vision and image analysis (Shu *et al.*, 2024; Meiseberg *et al.*, 2024; Mantovani *et al.*, 2024). EquiBreathe project has demonstrated the extraction of clinically-relevant respiratory motion features from smartphone video in horses (Gomes *et al.*, 2026).

Bioacoustic analysis is very attractive because of respiratory disease-related sound information. Microphones can be used for cough monitoring, respiratory cycle detection, and characterization of abnormal airway sounds. Traditional methods use the signal's amplitude, duration, frequency distribution, spectral descriptors, or Mel-frequency cepstral coefficient while DL is able to learn features of the spectrogram or waveform. Automated calf cough monitoring showed high specificity but limited sensitivity and illustrated the scalability and limitations of a group-level acoustic signal (Vandermeulen *et al.*, 2016; Carpentier *et al.*, 2018). In horses, DL-based respiratory event detection shows that acoustic monitoring can work during exercise where manual respiratory measurement is impossible (Parmentier *et al.*, 2026).

Wearable sensors and automated feeding systems provide continuous individual-level information. Accelerometers classify lying, standing, locomotion, rumination, feeding, and inactivity, while automated feeders measure milk intake, drinking speed, visit frequency, meal duration, and temporal feeding patterns. These variables are not specific for respiratory disease but can uncover sickness-related patterns (Cramer *et al.*, 2020; Bowen *et al.*, 2023; Bushby *et al.*, 2024; Bhujel *et al.*, 2025; Bhujel *et al.*, 2025). Thermal cameras provide non-contact thermal information. AI-aided localization of the eyes and muzzle makes possible to measure temperature repeatedly, despite environmental conditions, coat, head

position, airflow, and camera geometry influence (Kim *et al.*, 2025).

Multimodality is the major direction of the field. Respiratory disease is a multidimensional process biologically while each sensor provides partial information. Combining feeding, activity, respiratory motion, cough, temperature, environmental exposure, imaging, and clinical data might increase specificity. Data can be combined at early (before modeling), representation (at the representation level), or late (after predictions in modality-specific models) fusion stage. Multimodal systems are more robust but introduce additional challenges

related to synchronization, missing modalities, interoperability, computation, and interpretation. They are becoming increasingly emphasized in broader precision livestock AI research (Bertram *et al.*, 2023; Paulauskaite-Taraseviciene *et al.*, 2026; Distanto *et al.*, 2025; Tedeschi *et al.*, 2025; Mao *et al.*, 2026).

An overview of the principal sensing modalities, artificial intelligence approaches, respiratory phenotypes, and clinical outputs used for respiratory assessment in large animals is presented in Figure 1.

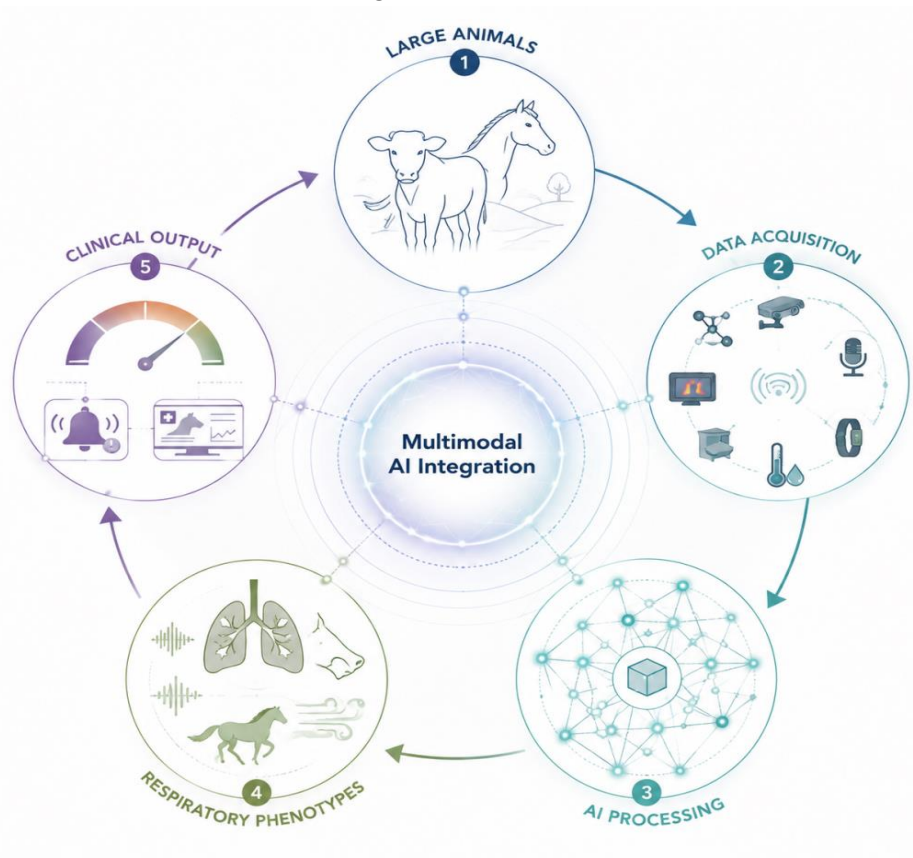


Figure 1: AI technologies for large-animal respiratory assessment.

Representative studies illustrating the current levels of evidence for AI-enabled respiratory assessment in large animals are summarized in Table 1.

The following categories of evidence differentiate between AI applications for

disease from disease screening, objective phenotyping or measurement of respiration, and supporting technology that has yet to be tested in respiratory disease.

Table 1: Representative studies with the current levels of evidence for AI-enabled respiratory assessment in large animals.

Species	Study / target	Sample size	Data modality	AI / analytical approach	Reference standard / target	Main findings	Evidence category	Ref.
Cattle	Subclinical respiratory disease	NR	Automated feeding behavior	Automated behavioral analysis	Thoracic ultrasonography	Feeding behavior changed in calves with subclinical pulmonary disease despite absence of obvious clinical abnormalities	Disease-associated screening	(Cramer <i>et al.</i> , 2020)
Cattle	Early BRD detection	106 calves	Automated feeder, pedometer, clinical observations, TUS	k-nearest neighbor	Clinical observations and thoracic ultrasonography	Behavioral features identified BRD-associated patterns several days before clinical diagnosis in selected modeling scenarios	Disease-associated prediction	(Cantor <i>et al.</i> , 2022)
Cattle	Early BRD detection	172 calves	Feeding, movement, and social behavior; 229 features	Gradient boosting	BRD status	Accuracy 0.773, sensitivity 0.625, specificity 0.872, and F1 score 0.689	Disease-associated prediction	(Bushby <i>et al.</i> , 2024)
Cattle	Respiratory disease detection	NR	Automated milk-feeder data	Deep convolutional neural network	Respiratory disease status	Sensitivity 0.826, specificity 0.790, accuracy 0.800, NPV 0.970, and PPV 0.365	Disease-specific AI	(Ghaffari <i>et al.</i> , 2022)
Cattle	Respiratory behavior monitoring	NR	Video	YOLO segmentation, CNN, and bidirectional LSTM	Respiratory behavior	Average accuracy approximately 93.6% under different test conditions	Respiratory phenotyping	(Wu <i>et al.</i> , 2023)
Cattle	Automated cough detection	NR	Continuous acoustic recordings	Automated acoustic analysis	Manually identified cough events	Sensitivity 50.3%, specificity 99.2%, and precision 87.5%; increased coughing preceded several BRD episodes	Respiratory phenotyping / screening	(Vandermeulen <i>et al.</i> , 2016)
Cattle	BRD management under commercial feedlot conditions	NR	Wearable ear-tag data	Proprietary AI-based disease detection	Conventional clinical management	Earlier first BRD treatment and some improvement in health outcomes; estimated net value increase of approximately US\$29.50/animal	Clinical decision support	(Schupbach <i>et al.</i> , 2025)
Horse	Equine asthma assessment	23 horses (12 asthma, 11 controls)	Smartphone video of nostril and abdominal motion	AI-based video analysis	Clinical asthma status	Best nostril-based model achieved 89% accuracy	Disease-specific proof-of-concept	(Gomes <i>et al.</i> , 2026)
Horse	Respiratory-event detection during exercise	NR	Microphone recordings during high-intensity exercise	Temporal convolutional network; LSTM; signal processing	Expiratory events	Median F1 score 0.94; respiratory-rate MAE 1.44 ± 1.04 breaths/min	Respiratory phenotyping	(Parmentier <i>et al.</i> , 2026)
Horse	Upper-airway dysfunction	NR	Endoscopy video	Cascaded YOLOv8, spatiotemporal features, decision-tree classification	Endoscopic upper-airway phenotype	Automated anatomical localization and classification of laryngeal dysfunction with explainable features	Disease-specific AI / phenotyping	(Tahir <i>et al.</i> , 2024)
Horse	Pharyngeal lymphoid hyperplasia	70 horses	Endoscopic images	Object-detection algorithms	Endoscopic lesions	Automated quantification of pharyngeal lymphoid hyperplasia was demonstrated	Disease-specific phenotyping	(Kozłowski <i>et al.</i> , 2025)
Horse	Respiratory-rate monitoring	NR	Wearable strain-gauge IoT sensor	Sensor-based respiratory analysis	Conventional respiratory-rate measurement	Good agreement with conventional measurement; ICC approximately 0.85	Respiratory measurement / enabling technology	(Farias <i>et al.</i> , 2025)
Sheep	Respiratory-rate monitoring	NR	Visible and near-infrared video	Non-contact motion-based analysis	Respiratory rate	Demonstrated feasibility of objective non-contact respiratory-rate monitoring	Respiratory measurement / enabling technology	(Bonafini <i>et al.</i> , 2024)

Table 1 (continued):

Species	Study / target	Sample size	Data modality	AI / analytical approach	Reference standard / target	Main findings	Evidence category	Ref.
Buffalo	Disease classification	NR	Clinical symptoms	Machine-learning classification	Symptom-based disease labels	Demonstrated ML-based disease classification, but respiratory signs were not specific for pneumonia	Enabling technology only	(Naik <i>et al.</i> , 2025)
Camel	Daily activity recognition	NR	Video	YOLOv7	Behavioral labels	High precision and recall for classification of daily activity	Enabling technology only	(Al-Khateeb <i>et al.</i> , 2024)
Camel	Automated behavior recognition	NR	Triaxial accelerometers and gyroscopes	Deep learning	Behavioral labels	Demonstrated automated recognition of dairy-camel behavior	Enabling technology only	(Aoun <i>et al.</i> , 2025)
Goat	On-farm health and welfare monitoring	NR	IoT sensing and video	Machine learning and video-based behavior recognition	Health/behavioral monitoring	Demonstrated a commercial monitoring platform, but no pneumonia-specific prediction was validated	Enabling technology only	(Rao <i>et al.</i> , 2020)

Abbreviations: AI, artificial intelligence; BRD, bovine respiratory disease; CNN, convolutional neural network; ICC, intraclass correlation coefficient; IoT, Internet of Things; LSTM, long short-term memory; MAE, mean absolute error; NPV, negative predictive value; PPV, positive predictive value; TUS, thoracic ultrasonography; NR, not reported in the current review text.

Artificial intelligence and bovine respiratory disease

Of all the respiratory conditions of large animals examined in connection with artificial intelligence and precision livestock farming, bovine respiratory disease (BRD) is undoubtedly the most extensively researched. The reasons for this trend go beyond the fact that BRD is frequent, economically important, and biologically complex. Modern dairy and feedlot facilities produce continuous high-frequency animal-level data. The goal of current studies, therefore, is not only to find signs of clinically visible disease but also to detect the preclinical behavioral and physiological deviations triggering targeted examination of the animal before the development of significant lung lesions or productivity decline (Cramer *et al.*, 2020; Bowen *et al.*, 2021; Duthie *et al.*, 2021; Bushby *et al.*, 2024).

Behavioral deviations as digital biomarkers

Behavioral changes are among the first signs of inflammation and infection. Cattle with

BRD may show decreased activity, increased immobility or lying time, alterations in the feeding behavior, reduced milk or fluid intake, fewer visits to feeders, changed distribution in the environment, or social isolation (Cramer *et al.*, 2020; Bowen *et al.*, 2021; Duthie *et al.*, 2021; White *et al.*, 2023; Bushby *et al.*, 2024). Duthie *et al.* analyzed the feeding and activity behavior of 100 pre-weaned dairy calves and found that behavioral deviations from the normal pattern preceded respiratory disease (Duthie *et al.*, 2021). Ramezani Gardaloud *et al.* (2022) further elaborated this idea studying 508 weaned calves and showed with the help of ear-mounted accelerometers that diseased animals exhibited increased inactivity several times before the disease onset, and longer lying time could be detected as early as five days before the clinical diagnosis (Ramezani Gardaloud *et al.*, 2022). Data from feedlots similarly show that sick cattle can exhibit altered activity, attendance at feeding and watering places, and social behavior (White *et al.*, 2023; Röschmann *et al.*, 2025). Thus, an important conceptual shift needs to occur in the future. Instead of

trying to detect some universal behavioral pattern indicating pneumonia, an efficient AI system should identify a multivariate deviation from the expected animal's behavior. Decreased walking distance may mean nothing in isolation but becomes important when combined with reduced intake, increased lying time, rising temperature, tachypnea, or cough. It is for this reason that the temporal parameters such as moving averages, the rates of changes, and deviations from individual baseline might be more informative than the absolute values of behavioral parameters.

Automated feeding devices and early prediction

Automated milk feeders are undoubtedly among the most effective sources of high-frequency data on early BRD. They continuously record total daily milk intake, intake per visit, drinking speed, visit duration, number of rewarded and unrewarded visits, inter-visit intervals, and feeding behavior temporal distribution. Cramer *et al.* (2020) found that the subclinically affected calves identified by thoracic ultrasonography showed changes in their automated feeding behavior even in the absence of obvious clinical abnormalities (Cramer *et al.*, 2020). This is especially clinically important since it means that the feeding data might carry information about lung disease even prior to visually evident disease manifestations. Combining feeding and activity data, Bowen *et al.* (2021) developed a predictive model based on moving-average deviation features and random-forest analysis which achieved high specificity, approximately 0.95, but lower sensitivity, approximately 0.54 (Bowen *et al.*, 2021). Applying gradient boosting and random forest to visit-level automated feeder data, Perttu *et al.* (2024) also

developed predictive models for BRD and found that the algorithms in question could achieve acceptable results despite the fact that results depended on the definitions of disease and the health information used as reference labels (Perttu *et al.*, 2024). These examples reflect the typical problem – feeding behavior is important for the screening purposes but usually should be combined with respiratory, thermal, movement, or clinical information.

Machine learning and deep learning for BRD

Machine learning algorithms make it possible to analyze several behavioral and physiological variables at once. Applying the k-nearest-neighbor algorithm to the data on 106 pre-weaned calves collected with the help of automated feeder, pedometer, clinical observations, and thoracic ultrasonography, Cantor *et al.* (2022) showed that behavioral features allowed for detection of BRD-associated patterns several days before the clinical diagnosis in some modeling scenarios (Cantor *et al.*, 2022; Cantor and Costa 2022). Casella *et al.* (2023) subsequently developed a machine-learning and optimization framework which took into account the costs associated with false positives and false negatives in the disease classification (Casella *et al.*, 2023). Using 172 group-housed calves, automated milk feeders, and ultra-wideband positioning sensors, Bushby *et al.* (2024) generated 229 features characterizing feeding, movement, and social behavior of the animals. As a result, gradient boosting showed the best results, with the accuracy of 0.773, sensitivity of 0.625, specificity of 0.872, and F1 score of 0.689 (Bushby *et al.*, 2024). The movement-related variables contributed approximately half of the top predictors, and the daily walking distance

was especially informative. The study is important for the fact that even the large number of input variables does not necessarily lead to close to perfect disease detection. Deep learning was also applied to calf's routinely collected data. Developing deep convolutional neural networks with the use of automated milk-feeder data, Ghaffari *et al.* (2022) achieved respiratory-disease sensitivity of approximately 0.826, specificity of 0.790, accuracy of 0.800, and negative predictive value of 0.970; however, the positive predictive value was much lower, approximately 0.365 (Ghaffari *et al.*, 2022). Such difference reflects the impact of the disease prevalence on screening performance. The algorithm in question can be very good at detecting animals who do not have the disease but can also generate quite a lot of false positives. Therefore, precision, predictive values, F1 score, calibration, precision-recall performance, and false alerts per animal-day should be reported in addition to accuracy.

Wearables, positioning devices, and spatial behavior

Ear, neck, or leg-attached accelerometers allow for continuous measurements of activity, inactivity, lying, standing, rumination, and locomotion without interfering with the animal's normal behavior. While the value of these sensors for respiratory medicine is not in the direct measurement of lung pathology but in the detection of sickness-associated change (Bowen *et al.*, 2021; Duthie *et al.*, 2021; Cantor and Costa, 2022; Ramezani Gardaloud *et al.*, 2022), ultra-wideband positioning devices additionally produce information on the distance travelled, speed, space use, attendance at feeders and drinkers, proximity to the pen mates, and duration of social contacts (White *et al.*,

2023; Bushby *et al.*, 2024). These spatial variables may be especially important for BRD as the disease is both an infectious and behavioral process – the diseased animals may reduce their movement and social contacts while proximity itself affects the transmission of pathogens. The principal limitation is the lack of specificity reduced activity may reflect diarrhea, lameness, heat stress, pain, or other systemic diseases. Therefore, wearable data are especially useful when AI analyzes them in combination with feeding, respiratory, thermal, acoustic, and environmental data, an approach reflected in the integrated IoT-based cow-health monitoring frameworks (Kaur and Virk, 2025). An effective clinically oriented system, accordingly, should differentiate between the "general disease" and "respiratory disease" signals.

Computer vision and respiratory phenotyping

Computer vision has considerable potential because the respiratory disease creates directly observable respiratory signs such as tachypnea, increased effort, abnormal posture, movement associated with coughing, nasal discharge, and reduced locomotion. Detecting abnormal respiratory behavior with the help of frame differencing and improved YOLOv5 architecture (Zeng *et al.*, 2023) developed the corresponding system. Using YOLACT-based segmentation, convolutional neural networks, and bidirectional LSTM components, Wu *et al.* created a more complex system allowing for monitoring respiratory behavior of multiple dairy cows with the accuracy of approximately 93.6% (Wu *et al.*, 2023). Shu *et al.* later developed non-contact monitoring system for the respiratory rate of multiple dairy cows kept in free-stall housing (Shu *et al.*, 2024), while

Mantovani *et al.* combined RGB and infrared video, fast Fourier transformation, and YOLOv8-based flank localization for the automated monitoring of the respiratory rate in unrestrained lying Holstein cows (Mantovani *et al.*, 2024). These examples show the shift of computer vision from the general behavior recognition to the objective respiratory phenotyping. However, tachypnea does not always equal BRD – heat stress, exercise, handling, fear, and pain can also cause it. Therefore, future models should take into account environmental temperature, humidity, recent activity, and individual baseline so that the tachypnea unexplained by the normal physiological context would receive higher disease weight than the high respiratory rate during the hot day.

Acoustic monitoring, cough detection, and thermography

Cough is a detectable respiratory sign and an easily scalable surveillance target for automation. Vandermeulen *et al.* (2016) developed a continuous cough-monitoring system with 50.3% sensitivity, 99.2% specificity, and 87.5% precision for coughs; an increase in coughing frequency preceded several clinically defined BRD episodes (Vandermeulen *et al.*, 2016). Carpentier *et al.* (2018) demonstrated automatic cough detection in calf-house settings during long-term recordings (Carpentier *et al.*, 2018). The greatest advantage of microphones is their ability to monitor several animals using a single device. The downside is individual attribution, which is possible only if there is synchronous localization or camera tracking of the coughing calf. Adding acoustic detection to cameras, RFID, positioning, or wearing microphones can significantly improve clinical utility of the cough data. Infrared thermography offers

complementary noncontact temperature data. Marquez *et al.* (2024) used facial thermography and behavioral variables to diagnose BRD (Marquez *et al.*, 2024), while Kim *et al.* (2025) applied Mask R-CNN to identify automatically the eyes and the muzzle to enable longitudinal thermographic monitoring (Kim *et al.*, 2025). As the surface temperature is affected by ambient temperature, airflow, solar radiation, coat, position of the head, and camera geometry, the most promising method would likely be analysis of within-animal temperature changes over time rather than interpretation of a single value of temperature. It becomes even more meaningful in combination with rising temperature trend and decreased activity, changed feeding, cough, or breathing rate.

Feedlot trials, multimodal systems, and decision support

Evaluation in the conditions of commercial feedlots is an essential step towards practical implementation of the technology. Schupbach *et al.* (2025) reported the results of 2025 feedlot trials comparing conventional pen riding with automated BRD management using wearable ear tag data and proprietary AI (Schupbach *et al.*, 2025). Cattle from the group monitored by the automated system showed reduced latency to the first BRD treatment and some improvement in adverse health outcomes. The authors also estimated the increase of the net financial value by approximately US\$29.50 per animal, although this economic difference was close but not clearly above the conventional statistical threshold. Given that the study was carried out in a single Oklahoma feedlot and with proprietary technology, it is necessary to conduct the trial elsewhere but it is still valuable due to its focus on clinical and

economic outcomes rather than retrospective classification only. Current studies tend to become multimodal. Brans *et al.* (2026) assessed integrated technologies and combined ML algorithms for early diagnosis of BRD in preweaned dairy-bred calves (Brans *et al.*, 2026). Multimodal system can combine the following: milk intake and feeding speed, distance traveled and lying time, social proximity, respiratory rate and effort, cough characteristics, eye or muzzle temperature, water intake, environment, clinical respiratory scores, thoracic ultrasonography, and laboratory findings. The aim is not just collecting more data but enhancing specificity of abnormality interpretation in the context. Mechanistic and uncertainty-aware methods are also emerging. Tabi *et al.* (2024) proposed a Bayesian deep-mechanistic framework for BRD diagnosis and forecasting with explicit addressing of noisy observations and uncertainty in the disease state (Tabi *et al.*, 2024). Merca *et al.* (2025) combined a mechanistic stochastic model of *Mannheimia haemolytica* transmission with the dynamic generalized linear modeling to assess risk-triggered treatment strategies (Merca *et al.*, 2025). Such approaches are especially relevant in case of BRD as the labels are noisy: an animal with a good clinical score can already have lung consolidation and clinical signs can indicate nonrespiratory diseases.

Diagnostic reference standards, validation, and clinical specificity

Quality of the reference diagnosis is one of the key limitations of BRD AI. The studies do not use a universal case definition: some apply clinical respiratory scores, some combine fever with clinical signs, others add thoracic ultrasonography or treatment records. The approaches identify different

but partially overlapping states of disease. An animal with clinical BRD according to visual scoring can have lung consolidation on ultrasonography, while another animal can show the signs of cough, fever, or depression but not having BRD. Consequently, the algorithm trained against visual scoring may learn the external manifestations of the disease rather than its internal pathology (Cramer *et al.*, 2020; Decaris *et al.*, 2022; Kamel *et al.*, 2024; Lindley *et al.*, 2025a). Subclinical pneumonia is especially relevant for early warning models. If the consolidation occurs before sickness behavior becomes obvious, then the thoracic ultrasonography can be used as a confirmation tool after identification of the abnormal animal using continuous surveillance. Practical approach would be to use automated feeding, activity, video, audio, and thermal data to screen cattle regularly and at low cost and then perform the clinical examination and ultrasonography of the animals with a high risk predicted. Such approach is more realistic as it does not expect the continuous sensors to provide a diagnosis. Validation also needs to avoid the data leakage. In longitudinal datasets, observations of the same calf are very correlated over the days. If records of one animal are included both in training and testing sets, then the performance is artificially inflated because the model recognizes the individual rather than the disease pattern. Animal-level partitioning should therefore be at least the minimum standard, followed by temporal validation, independent farm testing, multicenter validation, and ultimately real-time prospective evaluation (Paulauskaite-Taraseviciene *et al.*, 2026). It is especially relevant for BRD since the housing, breed, climate, management, sensor hardware, and prevalence of the disease differ significantly

in the farms. Risk probabilities should be calibrated and clinically interpretable. Instead of outputting the binary label of 'healthy' or 'BRD-positive', the system can produce a continuous probability estimate along with its uncertainty and key features driving the alarm. Low risk animals can stay under routine monitoring, intermediate risk animals can be re-evaluated, and high-risk ones can be examined by veterinarians. The selected threshold for action will depend on the prevalence of the disease, cost of missed cases, burden of false alarms, antimicrobial stewardship objectives, and availability of the confirmatory tests. Thus, in this situation, calibration and decision curve performance can be at least as important as discrimination. Multimodal context can also enhance diagnostic specificity. The tachypnea along with high ambient temperature, normal feeding, normal activity, and absence of cough is more consistent with physiological heat response rather than with BRD. In turn, the tachypnea associated with the decreased milk intake, decreased walking distance, repeated cough, and the increasing body temperature indicates the respiratory disease more strongly. The clinical value of AI therefore lies in distinguishing combinations and trajectories of abnormalities, not in alerting about any particular variable exceeding the population threshold.

Clinical perspective

The near future BRD AI application is continuous monitoring and prioritization of animals rather than autonomous diagnosis. The workflow would include continuous sensor surveillance, modeling of the individual baseline, detection of the abnormal physiological or behavioral changes, multimodal risk calculation, identification of high-risk animal, targeted

veterinary examination, and ultrasonography or laboratory testing of the animals if needed. Such approach allows the use of inexpensive or automated monitoring to identify animals who will probably need direct examination while maintaining the veterinary confirmation before antimicrobial administration. The future studies should therefore report not only model performance, but also lead time, missed cases, false alarms, treatment timing, antimicrobial exposure, health outcomes, labor requirements, and economic value. The proposed multimodal workflow for continuous BRD surveillance, risk stratification, and targeted veterinary assessment is summarized in Figure 2.

Artificial intelligence in equine respiratory diseases

Applications of artificial intelligence in equine respiratory medicine are not as developed as in BRD, but the recent literature demonstrates several clinically relevant approaches. Horses represent a unique possibility for digital assessment of respiratory function due to intermittent and nonobvious nature of many of their respiratory abnormalities. Equine asthma may vary from mild-moderate performance limitation to marked expiratory effort, while the diseases of the upper airways like recurrent laryngeal neuropathy, dorsal displacement of the soft palate, and pharyngeal collapse may manifest only during exercise (Lendl and Barton, 2024; Meiseberg *et al.*, 2024). AI is therefore especially valuable for objective phenotype extraction from videos, endoscopies, audio, wearables, exercise data, and environmental exposure.

AI-assisted assessment of equine asthma

Equine asthma is the clear example of

current disease-specific application. It is the syndrome of mild-moderate and severe inflammatory airway phenotypes with variable mucus accumulation, airway hyperresponsiveness, bronchoconstriction, cough, nasal discharge, increased abdominal expiratory effort, or poor performance

(Lendl and Barton, 2024; Meiseberg *et al.*, 2024). Clinical manifestation may not correspond to airway inflammation, especially in mildly affected horses, providing a rationale for objective digital phenotyping.

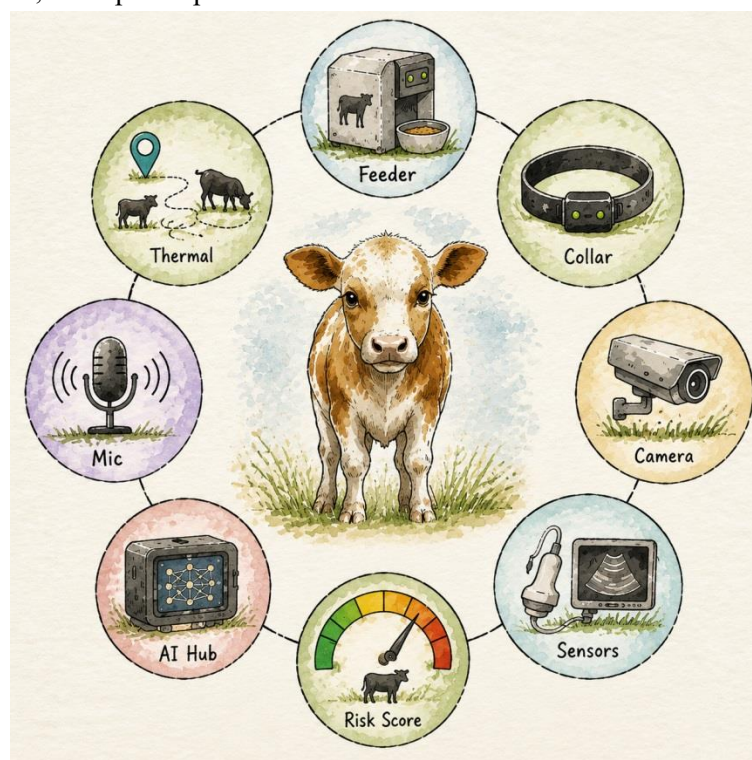


Figure 2: Multimodal AI framework for early detection of bovine respiratory disease.

Gomes *et al.* (2026) developed EquiBreathe – an AI-assisted approach to assessing equine asthma using the smartphone video of movement of the nostrils and abdominal regions (Gomes *et al.*, 2026). The proof-of-concept dataset included 23 horses, 12 with asthma and 11 healthy controls. The best nostril-based model demonstrated 89% accuracy. The significance of this study goes far beyond the numbers because it suggests that the ordinary smartphone videos contain sufficient information to quantify the subtle respiratory motion. Applications may include screening before veterinary examination, longitudinal monitoring of the known asthmatic horses, documentation of response to environmental modification or

treatment, and remote follow-up. However, the small size of the initial dataset requires its validation in multicenter studies involving different breeds, coat colors, severity of the disease, lighting conditions, camera positions, handlers, and distances.

Respiratory rate and post-exercise recovery as digital biomarkers

Measurement of a single resting respiratory rate only captures a small fraction of respiratory function. Exercise and recovery can expose hidden pathologies, which remain hidden otherwise. Röschmann *et al.* (2025) examined post-exercise recovery of respiratory- and heart-rates in standardized submaximal lunging exercise in horses with

neutrophilic airway inflammation and showed delayed respiratory-rate recovery (Röschmann *et al.*, 2025). This is important because a time series model would allow us to examine multiple aspects of recovery: peak respiratory rate after exercise, recovery speed back to normal levels, recovery slope, area under the recovery curve, workload, environmental variables, and interaction of respiratory and heart-rate recoveries. We could compare several training sessions with previous patterns for a particular horse. Individualized temporal phenotyping of this kind might be more sensitive in athletic horses with mild or transient disease than simple measurement of resting respiratory rate.

Respiratory bioacoustics during exercise

Bioacoustic analysis is another promising direction of development. Respiratory sound signals contain valuable information about airflow, respiratory cycle timings, airway narrowing, and upper airway function. Parmentier *et al.* (2026) compared performance of temporal convolutional neural networks, LSTMs, and classical signal processing in detection of expiration events from microphone recordings in high-intensity exercise in Standardbred trotters (Parmentier *et al.*, 2026). The temporal convolutional neural network achieved a median F1-score of 0.94 and estimated respiratory rate with mean absolute error of 1.44 +/- 1.04 breaths/min. The study is important because recordings were performed in real-life field conditions, not just in laboratory. Next step is disease classification. An acoustic respiratory system may be able to distinguish between physiological exercise-related sounds and patterns of horse asthma, recurrent laryngeal neuropathy, dorsal displacement of the soft

palate, or any other dynamic airway obstruction. Such application would require synchronized audio, endoscopy, workload, and expert diagnostic labels to train the algorithm on acoustic features of particular diseases rather than some general sounds or exercise intensity.

AI-assisted upper-airway endoscopy

Upper-airway endoscopy is one of the most promising directions of development in equine respiratory medicine, because many upper-airway pathologies depend on visual anatomy and dynamic motion. Endoscopic interpretation can be affected by many factors: image quality, endoscope placement and movement, anatomical perspective, and observer's experience. Tahir *et al.* (2024) developed an explainable machine learning framework for racehorse upper-airway analysis using endoscopy videos (Tahir *et al.*, 2024). In this work, they used cascaded YOLOv8 approach for anatomical region identification and segmentation, extraction of spatiotemporal features using landmark trajectories, and classification of laryngeal hemiplegia using decision-tree model. Explainability component is important because it allows understanding of the model's decision based on measurable anatomical and dynamic features rather than black-box scoring. Upper-airway dynamic disorders are especially suitable for spatiotemporal AI. Video endoscopy during exercise allows continuous recording in which machine learning algorithms could quantify left and right arytenoid position, rima glottidis opening, pharyngeal diameter, epiglottic position, dynamics of collapse, respiratory cycle phase in which dynamic disorder appears, and exercise intensity where this happens. This could transform qualitative grading to quantitative phenotyping and allow objective

comparison before and after therapy. Machine learning-assisted endoscopy is expanding also beyond disorders of larynx. Kozłowska *et al.* (2025) evaluated performance of object detection algorithms for automatic quantification of pharyngeal lymphoid hyperplasia from 70 horses' endoscopic images (Kozłowska *et al.*, 2025). Automatic system could potentially quantify the number, size, distribution, texture, and mucosa pattern of follicles, and thus transform endoscopy from descriptive procedure into source of quantitative biomarkers.

Wearables, smart textiles, and non-contact monitoring

Continuous respiratory monitoring in horses is complicated due to large body size, presence of fur, sweating, movement, displacement of equipment, and very high respiratory rate during exercise. However, modern devices and reviews of field monitoring shows that longitudinal data can be acquired practically (Farias *et al.*, 2025; Aarts *et al.*, 2026). Farias *et al.* (2025) developed Internet-of-Things device with strain gauge sensor of respiratory movements and wireless communication; the agreement with conventional respiratory rate measurements was good, with intraclass correlation coefficient approximately 0.85 (Farias *et al.*, 2025). These devices are not classifiers by themselves, but they can provide thousands of measurements in resting, exercise, transport, feeding, environmental exposure, and recovery for further machine learning analysis. Park *et al.* (2025) developed flexible smart textile band for continuous health monitoring of horses (Park *et al.*, 2025). Multi-sensor textiles are interesting because respiratory rate could be interpreted along with heart rate, movement, exercise, or temperature. Same elevated

respiratory rate has different meaning if heart rate has returned to normal levels, ambient temperature is high, horse performed unusual exercise, or if there is abnormal respiratory effort and sounds. Thus, multi-sensor context is important for distinguishing physiological reaction to exercise from pathology. Non-contact monitoring might be useful in stables, hospitals, quarantine facilities, and recovery areas. Millimeter-wave array radar has been used in proof-of-concept experiments to detect respiratory movements in horses without attachment (Matsumoto *et al.*, 2022), in accordance with more general developments of remote vital signs monitoring in veterinary medicine using radar, thermography, computer vision, and other AI-powered approaches (Zhao *et al.*, 2025). Radar-derived respiratory waveforms could be used in the future with AI to detect changes in rate and rhythm without disturbing the animal, however, large-scale validation experiments should be done.

Smartphones, environment, and personalized asthma monitoring

In combination with high-resolution cameras, microphones, accelerometers, gyros, connectivity, and significant computing power, smartphones are feasible platforms for multimodal assessment of equine respiratory system (Meistro *et al.*, 2026). Such an application can be built with video-derived nostril and abdominal motion, sound-derived respiratory sounds, exercise workload, Bluetooth heart or respiratory rate sensors, and clinical questionnaire. Such an approach is especially interesting in the case of repeated field assessment, since dedicated pulmonology equipment may not be available in such settings. Exposure to environmental factors is important in

assessing respiratory disease in horses. Dust, particles, mold-related substances, stability ventilation, forage, bedding, and season all affect airway inflammation and the development of clinical signs. Wearable particulate exposure sensors have already been tested in horses and can be correlated with respiratory rate, cough rate, nostril and abdominal motion, and post-exercise recovery. Thus, personalized models can estimate the impact of respiratory dysfunction after specific environmental exposure rather than considering the horse independent from its stable environment.

Computational fluid dynamics and other applications

While computational fluid dynamics is not AI per se, this technique can be considered as an important supplement to upper-airway disease. Tucker *et al.* (2024) performed computational fluid dynamics in equine head model to quantify consequences of recurrent laryngeal neuropathy and different surgical methods (Tucker *et al.*, 2024). The future system may be able to combine AI-driven anatomical segmentation from endoscopy or CT scan with airway reconstruction and airflow simulation. Thus, such a system may help comparing the severity of obstruction or treatment. Also, AI has been introduced to the problem of Exercise-Induced Pulmonary Hemorrhage (EIPH). Bertram *et al.* (2023) tested human experts against the deep-learning algorithm for cytological scoring of EIPH in horses, thus proving the possibility of AI application to structured cytological evaluation in this condition (Bertram *et al.*, 2023). However, there is little research into the use of computer vision techniques for automatic detection and grading of blood in the airway. Such a system may be able to detect the blood presence, segment areas of

interest, standardize endoscopic grading, perform comparisons between multiple evaluations, and correlate with speed and workload. There is little direct research on AI-based assessment of infectious respiratory diseases in horses. These conditions include equine influenza, equine herpes virus infection, strangles, and many other contagious respiratory diseases, which can cause fever, cough, nasal discharge, decreased activity, and impaired performance. In principle, a surveillance system for outbreaks can include body temperature, activity, acoustic cough analysis, respiratory rate, and horse-to-horse proximity. Such systems may prove useful in racetracks, competitions, breeding farms, and transport, but disease-specific prospective validation is needed.

Dynamic upper-airway phenotyping and other disease-specific applications

Dynamic airway diseases are especially well-suited for AI research since the clinically meaningful condition may only emerge at certain intensity of physical activity or respiratory phase. Overground and treadmill endoscopy produce continuous sequences in which different types of disorders may coexist. Such disorders include recurrent laryngeal neuropathy with exercise-dependent collapse, dorsal displacement of the soft palate, vocal-fold collapse, axial deviation of aryepiglottic folds, palatal instability, and nasopharyngeal collapse. AI analysis may continuously quantify arytenoid position, glottis opening, pharyngeal area, epiglottic position, the duration of collapse, collapse frequency, and the workload when an abnormality emerges. This will be richer representation of phenotype than categorical score based on manual evaluation of several frames.

AI can also help with longitudinal research. If the same horse is examined before and after surgery or training adjustment, the system can compare airway area and dynamics at standardized workloads and determine if functional obstruction has changed. Similar computer vision approach can be used for pharyngeal lymphoid hyperplasia, in which follicles' number, size, distribution, mucosal texture, and lesion pattern can be quantified with AI-based techniques (Kozłowska *et al.*, 2025). These metrics can decrease the variability of observation and provide structured outcomes for clinical research. The advantage of continuous monitoring over endoscopy is in the ability to monitor what happens outside the diagnostic procedure. A wearable or smart textile device can produce repeated respiratory and heart rate measurements during daily training, while smartphone video or radar can provide additional non-contact measurements of respiratory function (Matsumoto *et al.*, 2022; Farias *et al.*, 2025; Park *et al.*, 2025; Meistro *et al.*, 2026). Longitudinal models can learn the expected response of a particular horse to a specific workload and detect unusual increases in respiratory rate, delayed recovery, or abnormal respiratory effort compared to the previous history of that horse. This individualized approach is especially interesting in the case of mild asthma and poor performance in which resting abnormalities may be minor. Environmental exposure is important for the interpretation of equine asthma. The respiratory responses of a horse may depend on respirable dust, stable ventilation, bedding, forage, humidity, temperature, and season of exposure. By correlating particulate exposure with cough, nostril motion, abdominal excursions, respiratory rate recovery, and exercise data, AI may be

able to detect the exposure-response relationships in the same horse. Such model may be useful in distinguishing a consistent environmental trigger from daily variability and objective assessment of management measures such as changes in forage preparation and stable environment. Other disease-specific applications are promising but have not yet received enough validation. For example, deep learning-based cytological scoring has been proposed for EIPH (Bertram *et al.*, 2023), while computer vision approach is a research topic for this disease. Infectious respiratory disease can be tackled with combination of fever, activity, cough acoustics, respiratory rate, and network analysis at racetracks or breeding farms. However, the uploaded literature does not contain any clinically validated AI algorithms for these conditions. Thus, it is appropriate to describe them as research topics rather than diagnostic tools.

Multimodal clinical decision support and limitations

The most promising equine architecture is multimodal with a veterinarian in the loop. In case of an asthmatic or poor-performing horse, smartphone video may quantify nostril and abdominal motion, microphone can capture respiratory sounds, wearables can measure respiratory and heart rate, exercise data can characterize workload, and environmental sensors can measure the dust exposure. By integrating these data, AI system may give an estimation of respiratory risk probability, after which the diagnostic examination, endoscopy, bronchoalveolar lavage, pulmonary function test, and other diagnostics may confirm the disease. For dynamic upper-airway disease, exercise endoscopy will be a valuable high-specificity modality. However, the major limitation of this approach is data scarcity.

Studies of equine respiratory diseases usually involve fewer cases and greater heterogeneity than studies of cattle precision medicine. Also, the important disorders may be intermittent and exercise-dependent. Models trained on small, single-center datasets are vulnerable to differences in breed, cameras, sensors, environment, and workload. Therefore, the current equine AI should be considered as screening, measurement, or decision support technology. The priorities include

multicenter datasets, standardized asthma phenotyping, standardized endoscopic annotations, external validation, individual baseline models, and prospective studies that prove that AI influences the diagnosis, monitoring, treatment, or performance management. The major current and emerging AI-enabled approaches for respiratory monitoring and clinical decision support in horses are summarized in Figure 3.

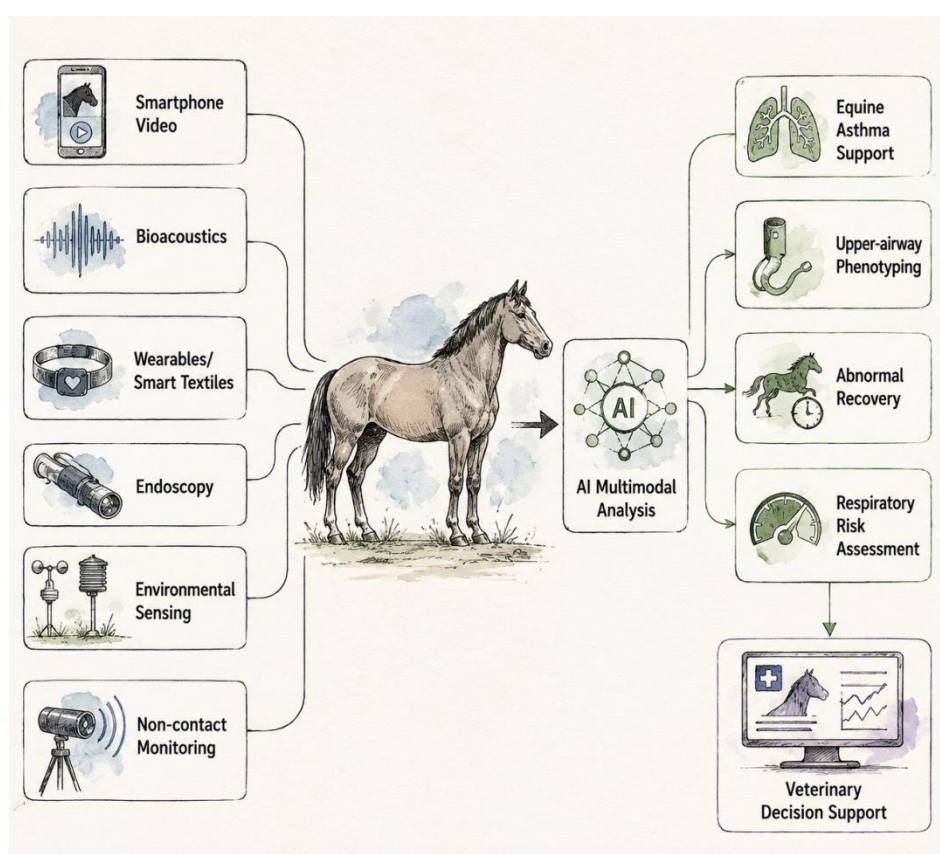


Figure 3: AI applications in equine respiratory medicine.

Buffaloes, camels, sheep, and goats

While there is very little evidence of respiratory AI in buffaloes, camels, sheep, and goats, various enabling technologies exist for future application. In particular, the important consideration is that successful behavior recognition or vital sign measurement cannot be considered as valid pneumonia diagnosis unless the AI

algorithm was linked to a proper respiratory disease reference standard. In sheep, Bonafini *et al.* (2024) developed an example of non-contact, motion-based respiratory-rate monitoring (Bonafini *et al.*, 2024). While such systems provide evidence that respiratory signals can be objectively measured in a non-contact manner, they can be further used in future pneumonia models

that will incorporate behavior, body temperature, acoustic data, and clinical assessment. In particular, the important need is the disease-specific validation in different housing and environmental settings. Naik *et al.* (2025) used ML algorithms for disease classification in buffaloes using symptoms (Naik *et al.*, 2025). However, such signs as fever, loss of appetite, depression, nasal discharge, and abnormal breathing are not specific to pneumonia. A more powerful model will include objective measurements of respiratory rate, body temperature, acoustic properties of coughing, activity, thoracic ultrasonography, and inflammation markers and/or blood test results. The use of thoracic ultrasonography is especially interesting in case of large ruminants since digital images can be used for future automated lesion detection and severity evaluation. The majority of camel AI research focuses on behavior and welfare. For example, Al-Khateeb *et al.* (2024) used YOLOv7 to classify the daily activity of dromedary camels with high precision and recall (Al-Khateeb *et al.*, 2024), while Moideen *et al.* (2025) used computer vision for behavior analysis related to stress response (Moideen *et al.*, 2025). Aoun *et al.* used triaxial accelerometers and gyroscopes with DL for automated behavior recognition in dairy camels (Aoun *et al.*, 2025). This technology could be used for development of sickness-behavior characteristics for pneumonia models, but the role of the environment must be considered since heat, dust, outdoor conditions, and large daily variations of these factors could impact respiratory rate and activity.

Rao *et al.* (2020) used Internet-of-Things sensing and ML as well as behavior recognition using video analysis in the commercial setting in goats (Rao *et al.*, 2020). Here, the contribution of the research

is in creation of the enabling platform and not in creating a pneumonia risk model. Future addition of respiratory-rate estimation, cough detection, body temperature, and veterinary diagnoses could make this platform useful for disease screening. The use of cross-species transfer learning could be helpful in reducing the data burden in less studied species, but the transfer from cattle cannot be assumed to be sufficient. Different species have different anatomy, behavior, coats, housing, exposure to the environment, and disease epidemiology. Therefore, transfer learning must be followed by species-specific fine-tuning and validation.

Multimodal AI and clinical decision support

Single-sensor systems generally suffer from a lack of specificity. Increased breathing rate may indicate pneumonia, heat stress, exercise, fright, and pain; reduced activity may be due to respiratory illness, lameness, enteric illness, and environmental stress; decreased feed intake is similarly non-specific. Multimodal AI tries to understand these factors in combination and their context (Bushby *et al.*, 2024; Brans *et al.*, 2026; Paulauskaite-Taraseviciene *et al.*, 2026; Mao *et al.*, 2026). For instance, tachypnea with reduced activity, frequent coughing, decreasing feed intake, rising temperature, and normal environmental heat load represents a distinct risk profile compared to tachypnea alone in a hot environment. Data fusion may take place at various levels. Early fusion combines engineered features before modeling, intermediate fusion combines learned features from the modalities such as video and audio data, late fusion combines predictions from separate modalities specific models. Various combinations are

possible. None of these approaches dominates, as selection depends on synchronization, missing data, sample size, computation, and the clinical objective (Mao *et al.*, 2026; Yilmaz, 2026). Longitudinal modeling is especially important. Population thresholds do not account for normal variability between animals. The individual-baseline models predict what is expected for a particular individual and detect deviations from the normal. This method is well suited for respiratory medicine, where the progression of the disease represents a process rather than a single event. It may also facilitate extrapolation across farms focusing on within-animal change. The multimodal systems require special validation. Observations of the same animal should not be split randomly into the training and test set, since a model may learn individual identification rather than disease patterns. The animal-level splitting is a minimal requirement for validation. More persuasive methods include temporal validation, external-farm validation, multicenter testing, and prospectively deploying (Paulauskaite-Taraseviciene *et al.*, 2026). Also, missing modalities have to be handled, since cameras, wearables, microphones, feeders, and Internet connectivity fail at different times. A clinical decision support system needs to produce more information than just an alarm. Ideally, it should produce a disease probability, its uncertainty, and the major contributing factors such as increased respiratory rate against the baseline, decreased walking distance, reduced milk intake, increased cough frequency, and temperature, which cannot explain tachypnea. Explainability will help veterinarians evaluate biological plausibility of a prediction and detect errors in the sensor data prior to issuing an alarm.

The integration with diagnostics of a higher specificity is a more feasible approach than striving to make the continuous sensors definitive. In calves, behavior, video, audio, and thermal monitoring can identify high-risk cases, followed by thoracic ultrasonography and clinical examination (Lindley *et al.*, 2025; Lindley *et al.*, 2025a; Lindley *et al.*, 2026).

Challenges and limitations to clinical implementation

The main limitation of veterinary respiratory AI applications is the quality of the dataset. Many studies contain relatively small numbers of animals from a single farm, institute, breed or region. Since respiratory diseases depend on age, management, immunity status, pathogens, environment, previous treatment and production systems, small samples put studies at risk of poor generalization (Hosseini-Zadeh, 2025; Xiao *et al.*, 2025). Another critical factor is diagnostic ground truth. Bovine Respiratory Disease can be diagnosed using clinical scores, presence of fever, medical records, thoracic ultrasonography or combinations thereof. A visually healthy calf may have lung consolidation, while an abnormal one may suffer from non-respiratory disease. The relationship between clinical symptoms, endoscopy, cytology, exercise test and environmental history in equine asthma also does not always correspond. AI can never be more accurate than the labels it is trained on. Class imbalance and low prevalence of the disease make the accuracy meaningless. A classifier may simply assign the majority class to the majority of animals, thus having very high accuracy. Evaluation of the classifier in the clinical setting should thus include sensitivity, specificity, precision, predictive values, F1, calibration, precision-recall performance, alerts per

animal day, lead time before diagnosis and consequences of misdiagnosis. Calibrated probability is especially important when an algorithm predicts if an animal needs to be clinically evaluated or treated. External validation and domain shift are still big issues. Differences in housing conditions, illumination, camera height, microphone location, sensor manufacturer, climate, breed and management may affect performance of the classifier. A model should therefore be evaluated using animals, farms and periods of time it has not been exposed to. The strongest design is prospective real-time studies, followed by external validation and comparison of AI-guided decision-making with traditional clinical surveillance. Reliability of sensors, availability of data, connectivity and interoperability are practical problems. Different sensor manufacturers may use proprietary formats, and rural areas may suffer from limited connectivity. Edge computing can solve the issue of transmitting large amounts of video or audio, as data can be processed in place and only results are transmitted. Cybersecurity and data governance become ever more important as digital livestock systems will store animal level, production, treatment and commercial data (Neethirajan, 2025). Explainability and professional responsibility are key issues when AI affects antimicrobial use or decision-making in high-stake situations. A veterinarian must understand whether the alert is based on a valid pattern of respiratory activity or poor data quality. Ethical assessments of veterinary AI algorithms stress the importance of accountability of a human being who uses the technology and should explain his/her decisions (Coghlan and Quinn, 2024; Heinlein, 2026).

Ultimately, economic feasibility drives implementation. Cost of hardware, maintenance, connectivity, cost of training staff, false alerts, labor savings, antimicrobial savings, performance and clinical outcome are part of the cost. The success of any algorithm will depend on its ability to integrate into existing workflows, produce a reasonable number of alerts and help to achieve enough benefits to pay off.

Future firections and tesearch priorities

The next generation of respiratory AI for large animals needs better evidence and not just better models. Datasets from multiple centers are required across breeds, farms, seasons, production systems, sensors and platforms, and disease severity, with synchronized multimodal data annotated with accurate clinical reference diagnosis and imaging and treatment outcomes if applicable (Ferreira *et al.*, 2024; Bhujel *et al.*, 2025; Distant *et al.*, 2025; Tedeschi *et al.*, 2025). Similar emphasis on multimodality, collaboration, and AI platform sharing is evident in the broader livestock AI literature for generalizability of models beyond a single farm or species (Nasser and Kasper, 2026; Zhao *et al.*, 2026). Standardized respiratory disease labels are needed. Harmonized criteria, based on clinical examination and thoracic ultrasonography, for bronchopneumonia would improve comparability. For horses, standardized asthma phenotype definition and consistent annotation of upper airway endoscopy would enable larger shared datasets. The immediate need for buffaloes, camels, sheep and goats is creation of species-specific respiratory datasets, not adoption of models from elsewhere. Federated learning could make it possible to train models without centralized raw data

from multiple farms or institutions (Garro *et al.*, 2025; Ganesan *et al.*, 2026). Transfer learning could decrease the amount of data required by training models on relevant tasks or species, but the model needs to be validated afterwards in the species and the domain of interest. The concepts of foundation-models, continual learning and digital twins have emerged as novel approaches to precision livestock farming (Abdelrahman *et al.*, 2026; Cabrera and Niu, 2026; Garcia and Robles, 2026; Neethirajan, 2026) and they should be assessed against simple baselines and clinically relevant outcomes. Edge AI could be crucial for real-time respiratory monitoring. Local computation can be used to decrease bandwidth and latency for cough detection, respiratory rate estimation and camera-based alerts. Hybrid edge-cloud systems could deliver instant alerts to farms while using cloud computing power for modeling of the population and updating the models (Guo *et al.*, 2026).

Individualized predictions should be a goal in the future. Instead of asking whether the respiratory rate is higher than some universal threshold, future models could estimate the expected respiratory rate of a particular animal given workload, environmental conditions, time of day, age, and prior measurements and quantify the

deviation from the expected value. It could improve the recognition of disease and lower number of alerts due to physiological variations. Future systems should also evolve from mere detection to prognosis and treatment response monitoring. Clinically relevant questions are: can AI predict which calves will develop lung consolidation, which horses will experience asthma-related dysfunction persistently, can AI quantify objective treatment response and whether AI-guided surveillance will decrease antimicrobial use without increasing missed disease. The human-in-the-loop design should be at the center of the efforts. The preferred approach is not autonomous treatment but continuous AI-based screening followed by focused veterinary assessment. Prognostic studies comparing AI-assisted management to standard care should be designed prospectively, assess the health and welfare of the animals, antimicrobial use, production or performance, labor costs, false alert burden, and economic outcomes. Transparency in preprocessing, validation, missing data handling, and model performance is essential. The principal barriers to clinical translation and the major priorities for future development of respiratory AI are summarized in Figure 4.

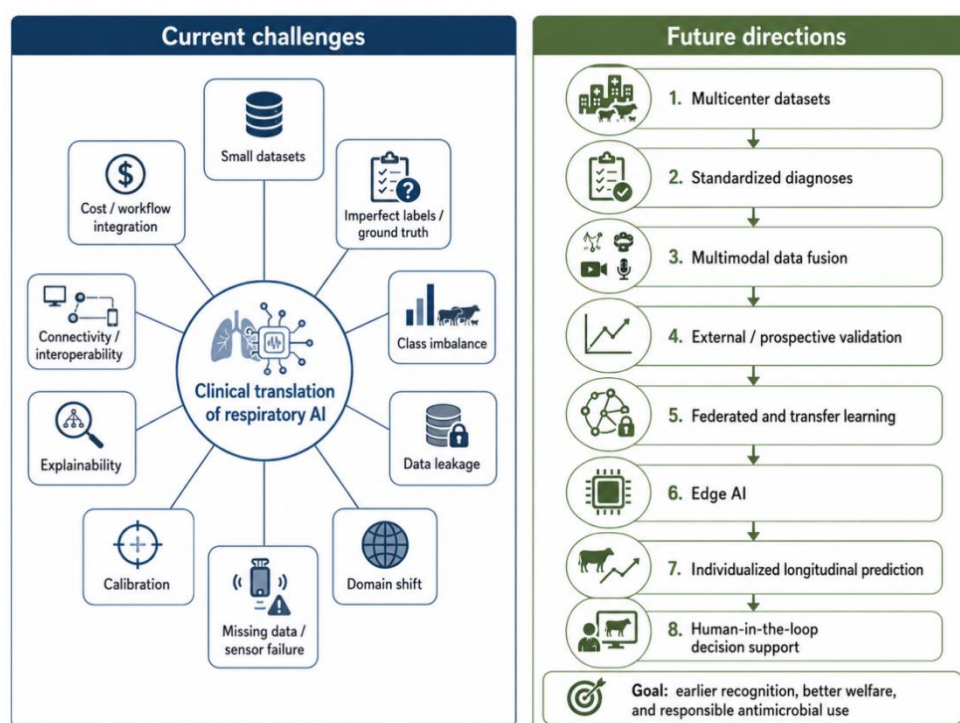


Figure 4: Current challenges and future roadmap for artificial intelligence in large-animal respiratory medicine.

Conclusion

The use of AI is making it possible to monitor the respiratory health of large animals continuously in an objective way and based on data rather than episodic clinical examinations only. The most compelling evidence to date is with BRD, where feeding system, accelerometry, positioning, computer vision, acoustic sensing, thermography, and machine learning have been used to detect behavior and physiology associated with the disease. In horses, smartphone video capture, respiratory bioacoustics, AI-assisted endoscopy, wearables, and non-contact monitoring are emerging clinically relevant techniques. The evidence in buffaloes, camels, sheep, and goats is sparse and should not be seen as a basis for respiratory diagnosis but for disease-specific research in the future. The field is evolving from the use of one sensor modality to multimodal and longitudinal phenotyping. Combining data from respiration, behavior, temperature,

acoustic sensing, environment, imaging, and clinic can provide more specific information and enable personalized risk assessment. Yet, small training data sets, label inconsistency, class imbalance, data leakage, domain shift, missing sensor information, calibration, explainability, costs, and integration in the clinical workflow pose significant challenges. AI should thus be used to support decision-making rather than as an autonomous tool. Clinically relevant systems will continuously detect abnormal changes, rank animals at the highest risk, explain their rationale and uncertainty, and draw attention of veterinarians to animals in need for an examination or testing. The ultimate criterion of progress should be better disease recognition, increased diagnostic efficiency, improved animal welfare, responsible use of antimicrobials, and economic gains rather than just algorithmic sophistication.

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Conflict of interest

The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this manuscript.

AI and AI-assisted technologies declaration: The authors used ChatGPT (GPT-5.6, OpenAI) to assist with idea generation, editing, and improving the text of this work. Additionally, GPT Image 2 was used to assist in the creation and preparation of the figures.

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