

MANAGEMENT AND SUSTAINABILITY: *Invited Review*

INVITED REVIEW: Precision livestock farming technologies in swine intensive production

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ABSTRACT

Purpose: The intensification of swine production has raised concerns about animal welfare, environmental impact, and productivity. Precision livestock farming (PLF) technologies offer innovative solutions by leveraging sensors, automation, and artificial intelligence to enhance monitoring and management in pig farming. This review explores the current state of PLF applications in swine production, identifying key benefits and challenges associated with their implementation.

Sources: This review is based on a systematic analysis of peer-reviewed literature, including studies published between 1990 and 2024. Data were gathered from electronic databases such as PubMed, Web of Science, and Scopus, focusing on technologies for health monitoring, feeding optimization, microclimate control, and welfare assessment in pigs.

Synthesis: Precision livestock farming technologies have demonstrated their potential to improve productivity, health, and welfare through early disease detection, automated feeding, and environmental control. Camera-based systems, sound analysis, and radio-frequency identification tracking enhance real-time monitoring, and predictive maintenance reduces system failures. However, adoption remains limited because of high costs, technical complexity, and the need for producer training.

Conclusions and Applications: Precision livestock farming represents a promising approach for optimizing swine production, but broader adoption requires cost-effective solutions and interdisciplinary collaboration. Future research should focus on integrating PLF tools into practical farm settings, ensuring accessibility and user-friendly implementation to support sustainable and ethical pig farming.

Key words: sensor, pig farming, animal welfare monitoring, smart farming, predictive maintenance

INTRODUCTION

In recent years, global livestock production systems underwent significant intensification, increasing both productivity per animal and the number of animals raised. This trend sparked concerns by consumers regarding food safety, sustainability of livestock supply chains, animal welfare, and public health (Liu et al., 2023). Although highly organized and efficient intensive production systems offer opportunities to enhance animal welfare and adopt sustainable practices, these benefits often conflict with issues such as biodiversity loss, land use changes, and environmental sustainability (Tichit et al., 2011; El-desouky et al., 2018; McNicol et al., 2024). Within this context, the global pig production sector plays a pivotal role in meeting the increasing demand for animal protein, making it an ideal candidate for precision livestock farming (PLF) technologies aimed at improving efficiency and sustainability (Tzanidakis et al., 2021). The relatively short production cycle of pigs enables rapid evaluation of technological interventions, offering unique opportunities to test and refine PLF solutions. However, despite these potential benefits, the adoption of precision technologies in pig farms remains limited. This review aims to explore the state of precision technologies in pig farming, focusing on their applications in operational efficiency, environmental management, and welfare monitoring, as well as the barriers to their widespread adoption. Additionally, we propose strategies for broader implementation, emphasizing the role of interdisciplinary research in driving progress.

In swine farming, PLF encompasses advanced technologies such as sensors, robotics, and data analytics to monitor and optimize animal health, welfare, and productivity (El-Sabrou et al., 2024). Recent advancements, including automated environmental monitoring systems and real-time feeding automation tools, have shown promise in re-

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ducing resource waste and improving productivity (Remus et al., 2020; Li et al., 2023). Additionally, wearable sensors and artificial intelligence (AI)-driven analytics have enhanced reproductive efficiency and early disease detection in pigs (Chung et al., 2013; Zhang et al., 2022; Wang et al., 2024). Despite these advancements, technological applications in pig production are predominantly concentrated at the top of the production pyramid, targeting facilities managing breeding stock of high genetic and economic value. Broader adoption at the level of individual animals within diverse production systems is still limited, partly because of intrinsic characteristics of pig farming, such as spatial distribution and stocking density, and partly because of farmers' reluctance to invest in advanced technologies (Rowe et al., 2019; Kopler et al., 2023). Another possible reason concerns the relatively high density of pigs in a barn, low economic value, and short productive life of individual pigs (compared, for example, to dairy cows), which makes the application of sensors on individual animals less economically viable.

The increasing number of pigs per farm requires increased labor to ensure optimal management, emphasizing the importance of standardized operating procedures to maintain high quality standards. Precision livestock farming systems must address the needs of end users, ensuring that the generated recommendations or alerts are directed to the appropriate individuals, whether farm owners or caretakers. Moreover, large pork-producing enterprises often prioritize risk minimization and cost reduction (particularly for feed, which represents a substantial operational expense), whereas consumers demand sustainable production, reduced carbon footprint, and improved animal welfare.

Pig farming faces significant health and welfare challenges, such as piglet crushing, tail biting, and respiratory issues (Albernaz Gonçalves et al., 2021; Bagaria et al., 2022; Kobek Kjeldager et al., 2023). For example, sows' inability to build nests in most housing systems increases the risk of piglet crushing (Liu et al., 2022). Studies using accelerometer technology to monitor nest building behavior demonstrate the potential to limit confinement in farrowing crates to the first days after farrowing, thereby improving animal welfare (Oczak et al., 2015). However, improving the design of crate and free-farrowing pens to minimize crushing should be the primary intervention. Tail and ear biting in postweaning and finishing pigs are other critical welfare concerns, exacerbated by stress, overcrowding, and poor microclimatic conditions (Nannoni et al., 2023). Automated systems using 3D cameras and computer vision show promise in the early detection of tail-biting behavior, enabling timely interventions (D'Eath et al., 2018; Hakansson and Jensen, 2023). Similarly, respiratory issues, common in weaned and finishing pigs, can be mitigated through microclimate control and the use of cough-detection microphones (Chae et al., 2024).

This systematic review was conducted in accordance with the guidelines of the Preferred Reporting Items for System-

atic Reviews and Meta Analyses (PRISMA) statement to ensure transparency and reproducibility throughout the research process (Moher et al., 2009; Figure 1). A comprehensive search was performed across multiple electronic databases, including PubMed, Web of Science, and Scopus, to identify relevant studies published between 1990 and 2024. The search strategy employed a combination of key words and Boolean operators ("AND" and "OR"), with the key words "precision farming," "precision agriculture," "swine," "pig farming," "technology," "smart farming," and "data driven farming." To ensure thoroughness, the reference lists of retrieved articles were also screened for additional relevant studies. Only peer-reviewed publications, including original research articles and conference proceedings, were included in this review. Eligible studies focused on the application of precision farming technologies in pig production systems and addressed topics such as health monitoring, feeding automation and optimization, microclimate control, or reproductive management. Studies that did not cover these topics, were not published in peer-reviewed sources, lacked full-text availability, were classified as gray literature not subjected to peer review, or were not in English were excluded from the review.

APPLICATION OF PRECISION TECHNOLOGIES IN PIG FARMING

In PLF, wearable technologies designed for individual animals dominate the market (Zhang et al., 2021). However, in systems with a lower economic value per animal (such as those involving pigs, poultry, rabbits, and fish), group-level monitoring tools, including cameras or robots, are more commonly used instead of individual-level devices (Halachmi et al., 2019). Pigs are typically housed in groups ranging from 10 to over 100 individuals, making individual monitoring particularly challenging. For this reason, in growing and finishing pigs, most PLF systems are designed for group-level monitoring, whereas some systems for sows focus on individual monitoring. Currently, sensors dedicated to individual animals remain prohibitively expensive, but costs may decrease in the future with the widespread adoption of such technologies. Group monitoring, therefore, appears to be the primary focus of current development efforts. Advanced software techniques, such as machine learning and deep learning, facilitate the collection of vast amounts of data, which are then transformed into actionable insights aimed at improving animal welfare and productivity (Benjamin and Yik, 2019; Halachmi et al., 2019).

Monitoring Animal Variables

Technologies for PLF have significantly advanced the ability to monitor key variables in livestock farming, providing tools to assess animal health, welfare, and productivity with greater accuracy and timeliness (Gómez et al., 2021; Akinyemi et al., 2023). Monitoring animal variables

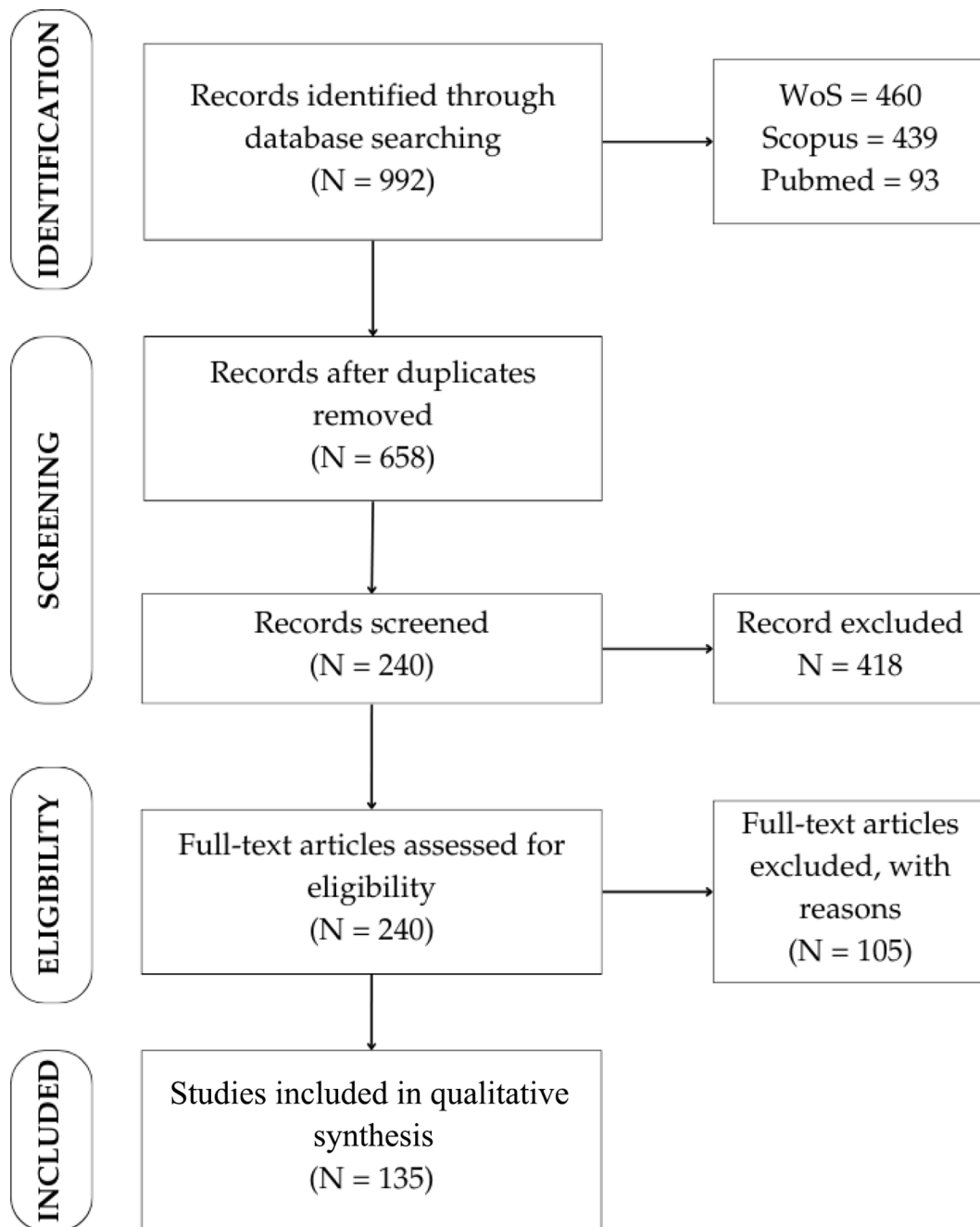


Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta Analyses) flow diagram of the study selection process. WoS = Web of Science.

is crucial for detecting early signs of illness, optimizing resource use, and improving overall farm management. These technologies leverage a range of sensors, imaging systems, and data analytics to capture information at both the group and individual levels, enabling farmers to make informed decisions (Dineva and Atanasova, 2022). In pig farming, the variables monitored include physiological parameters (such as body temperature and heart rate), behavioral indicators (such as activity patterns and feeding behavior), and environmental parameters (such as thermal comfort and air quality). The integration of these data streams enables comprehensive assessments of

animal well-being and performance, offering opportunities to address challenges in disease management, stress reduction, and production efficiency. This section explores the diverse array of technologies and approaches developed for monitoring animal variables in pigs. Each subsection focuses on a specific technology or method, discussing its principles, applications, and potential to enhance precision management in pig farming.

Camera-Based Monitoring. Image analysis has demonstrated significant potential for monitoring livestock since the early 1990s (Van der Stuyft et al., 1991). At the core of camera-based technologies lies software: whereas

cameras capture images, software interprets and transforms them into actionable data and insights (Arulmozhi et al., 2021). These systems offer a distinct advantage because they do not require sensors to be worn by the animals, thereby avoiding additional stress (Norton et al., 2019). Camera-based techniques provide innovative, non-invasive solutions for monitoring animal behavior, position, distribution, and activity within enclosures (Shaik Mazhar and Suseendran, 2021). Such methods enable continuous observations and are particularly advantageous in intensive farming systems where human monitoring is impractical (Fernandes et al., 2020). Captured images have been analyzed to determine spatial arrangements and the proportion of pigs occupying different areas of their enclosures, offering valuable insights into behavior and responses to environmental conditions (Chung et al., 2014; van der Zande et al., 2021). However, pig farming environments often present challenges for image detection technologies, including poor lighting, low contrast between pigs and flooring, interference from environmental factors (Tuytens et al., 2022), and a harsh environment that hinders the long-term use of cameras. Advanced machine learning algorithms have significantly improved the reliability of image interpretation under varying conditions (Marsot et al., 2020). A summary of the main studies on the application of image analysis in pig farming is presented in Table 1, summarizing the methodologies, technologies, and specific applications in the swine industry.

Image analysis has proven particularly useful in measuring critical bioresponses, such as health (Islam et al., 2015; Martínez-Avilés et al., 2017), behavior, welfare (Gronskyte et al., 2015; Tu et al., 2024), and growth parameters (Nasirahmadi et al., 2019). These systems play a crucial role in assessing environmental factors that affect animal welfare, such as thermal stress (Schmidt et al., 2013; Zhang et al., 2021). For instance, observing a high concentration of pigs lying in dirty areas of the pen, typically reserved for defecation, rather than in designated resting zones, can indicate suboptimal climatic conditions (i.e., too hot temperature, Nilsson et al., 2015). In fact, pigs may lie in cooler, moist areas to dissipate heat, even though these zones are typically avoided because of the presence of excreta and reduced air quality. Such behavior highlights environmental deficiencies requiring immediate intervention. Similarly, in piglets, image analysis can be used to monitor huddling behavior in response to disease or cold temperatures (Cook et al., 2018). By detecting these patterns, image analysis systems provide a powerful tool for real-time monitoring and climate management, ensuring that environmental conditions align with the animals' needs.

Monitoring pigs' locomotion through different technologies serves multiple purposes, including the detection of play and lying behaviors (Lind et al., 2005; Kashiha et al., 2014b) and lameness (Grégoire et al., 2013; Nalon et al., 2013). By applying advanced time-series analysis and machine learning models to longitudinal data, camera-based

systems can identify subtle deviations in gait and posture that precede the clinical onset of lameness, enabling early intervention and potentially preventing the development of fully developed disease (Nasirahmadi et al., 2017). Lind et al. (2005) developed one of the earliest software tools for image-based locomotion assessment, combining image subtraction and automatic threshold detection. A limitation of this approach, however, was that pigs had to be handled to walk individually in front of the camera. Later, Kongsro (2013) introduced a top-down image processing technique that automatically cropped images to focus on the animal, converted them to grayscale, and applied background subtraction. Movements were tracked using body width curves, and locomotion was defined through ellipse fitting methods, normalized to pig body length. Nasirahmadi et al. (2015) further refined this technique to identify moving pigs during lying periods.

At the group level, locomotion has been quantified through activity indices (Ott et al., 2014), where overhead camera images were processed by background subtraction and binarization, followed by morphological noise filtering. Gronskyte et al. (2015, 2016) applied optical flow analysis to quantify pig movement patterns, integrating optical flow estimation, animal identification, feature extraction, and frame classification. Their support vector machine model achieved high sensitivity (93.5%) and specificity (90%) in commercial scenarios, with an overall error rate of 6.5%. Depth cameras have also been investigated for lameness detection. Stavrakakis et al. (2015a) used a Vicon 3D optoelectronic system to characterize gait alterations in lame pigs, which were then compared with Kinect-based measurements (Stavrakakis et al., 2015b). Reflective markers were placed on anatomical landmarks, and Kinect data showed robust agreement with Vicon outputs ($r = 0.994$; $P < 0.001$), confirming its potential for farm use. Similarly, Kashiha et al. (2014b) used overhead cameras to track piglets, achieving 89.8% accuracy in locomotion classification.

Beyond locomotion monitoring, recent advances in computer vision have focused on automated scoring of feet and leg structure for lameness prediction and detection; lameness remains a leading cause of culling and productivity loss in breeding herds (Willgert et al., 2014). van Riet et al. (2019) proposed a mobile claw scoring device as a stress-reducing, on-farm alternative for scoring claw lesions. Despite requiring optimization, the system represents progress toward the automated assessment of conformational soundness. Complementarily, Peppmeier et al. (2025) demonstrated that imaging systems can objectively phenotype claws and legs, providing continuous and non-invasive monitoring, with possible applications to genetic selection for robustness and longevity.

Recent studies also highlight the role of deep learning-based posture estimation. de Paula et al. (2024) developed a repository of 2D video images with expert-assigned locomotion scores and trained computer vision models to identify lateral and dorsal postures of sows. Using LEAP

Table 1. Overview of main studies on image analysis techniques in pig farming¹

Type of data ²	Used tool ³	Application ⁴	Animal category ⁵	Reference
BC	Depth images	Ma	Pi	Chung et al., 2014
BC	Depth images	Pb, Tb	So	Lao et al., 2016
BC	Depth sensor	MAi	Pi	Lee et al., 2016
BC	Computer vision	MAi	Gp	Chen et al., 2017
BC	Depth images	TB	Gp	Matthews et al., 2017
BC	3D camera	MAi	Fp	Chen et al., 2019
BC	2D camera	Tm	Gp	Wutke et al., 2020
BC	Depth images	TBW	Gp	Zhang et al., 2020b
Bt	IRt	FI	Gp	Loughmiller et al., 2005
Bt	IRt	De	So	Scolari et al., 2011
Bt	IRt	De	So	Sykes et al., 2012
Bt	IRt	PS	Pi	Kammersgaard et al., 2013
Bt	IRt	De	So	Luño et al., 2013
Bt	IRt	WA	Fp	Weschenfelder et al., 2013
Bt	IRt	LAi	So	Amezcuca et al., 2014
Bt	IRt	PS	Pi	Caldara et al., 2014
Bt	IRt	DD	Fp	Siewert et al., 2014
Bt	IRt	De	So	Simões et al., 2014
Bt	IRt	DD	Gp	Cook et al., 2015
Bt	IRt	DD	Pi	Islam et al., 2015
Bt	IRt	GRd	Pi	Sasaki et al., 2016
Bt	IRt	TBW	Gp	Cook et al., 2018
Bt	IRt	DD	Pi	Lu et al., 2018a
Bt	IRt	MAi	Gp	Boileau et al., 2019
Bt	IRt	WA	So	Feng et al., 2019
Bt	IRt	WA	Pi	da Fonseca et al., 2020
Bt	IRt	DD	Gp	Jia et al., 2020
Bt	IRt	DD	Gp	Jorquera-Chavez et al., 2020
Bt	IRt	PS	Pi	Schmitt and O'Driscoll, 2021
Bt	IRt	WA	So	Staveley et al., 2022
Bt	IRt	DD	So	Stukelj et al., 2022
Bt	IRt	EPO	So	Gulliksen et al., 2023
Bt	IRt	PS	Pi	Küster et al., 2023
Bt	IRt	PS	Pi	Xiong et al., 2023
Bt	IRt	TBW	Gp	de Fátima Araújo Alves et al., 2024
Cl	MCDS	CHe	So	van Riet et al., 2019
Dv	2D camera	DB	Gp	Kashiha et al., 2013a
FoT	2D camera	FB	Gp	Yang et al., 2018
It	2D camera	Tm	Pi	McFarlane and Schofield, 1995
It	2D camera	Tm	Gp	Tillett et al., 1997
It	2D camera	Tm	Gp	Ahrendt et al., 2011
It	2D camera	ID, Tm	Pi	Kashiha et al., 2013b
It	CCD camera	Tm	Gp	Kashiha et al., 2014b
It	CCD camera	BWe	Gp	Kashiha et al., 2014a
It	CCD camera	TBW	Gp	Ott et al., 2014
It	CCTV camera	MAi	Gp	Nasirahmadi et al., 2016
Le	2D camera	MAi, Tb	Carcass	Blömke et al., 2020
LI	2D camera	DD	Carcass	Bonicelli et al., 2021
LP	2D camera	Tb, CTC	Gp	Nasirahmadi et al., 2015
LP	2D camera	DD, WA	Gp	Nasirahmadi et al., 2017
Pa	2D camera	BWe	Gp	Schofield, 1990
Pa	2D camera	LWd	Gp	Wang et al., 2008
PaW	CCD camera	GRd	Gp	Schofield et al., 1999
Pd	2D camera	LWd	Gp	Brandl and Jørgensen, 1996
Pdet	2D camera	CTC	Pi	Xin, 1999
Pdet	2D camera	Dm, CTC	Pi	Shao and Xin, 2008
Pdet	Depth images	MB	So	Zheng et al., 2018
Pdet	2D camera	TBW	Gp	Nasirahmadi et al., 2019

Continued

Table 1 (Continued). Overview of main studies on image analysis techniques in pig farming¹

Type of data ²	Used tool ³	Application ⁴	Animal category ⁵	Reference
Pdet	Depth images	Mip	Gp	Sa et al., 2019
Pdet	2D camera	Mip	Gp	Zhang et al., 2019
Pdet	2D camera	FB	Gp	Alameer et al., 2020
Pdet	2D camera	TBW	Pi	Li et al., 2020
Pdet	2D camera	TBW	Gp	Riekert et al., 2020
Pdet	2D camera	TBW	Gp	Shao et al., 2021
Pdet	2D camera	TBW, Tb, PS	So	Girardie et al., 2023
PDS	2D camera	GRd	Gp	Doeschl-Wilson et al., 2004
PDS	Depth images	BWe	Boars	Kongsro, 2014
PDS	CCD camera	LWd	Gp	Wongsriworaphon et al., 2015
PDS	Depth images	BWe	Barrows	Shi et al., 2016
PDS	3D camera	Bm	Gp	Guo et al., 2017
PDS	Depth images	Me	Gp	Condotta et al., 2018
PDS	3D camera	LWd	Gp	Lu et al., 2018b
PDS	2D camera	BWe	Gp	Pezzuolo et al., 2018
PDS	Depth images	BSe	Gp	Wang et al., 2018
PDS	2D camera	GSe	Gp	Zhang et al., 2020a
PDS	CCD camera	Gd	Gp	Win et al., 2021
PDS	2D camera	BCSd	So	He et al., 2023
PDS	2D camera	BWe	Gp	da Cunha et al., 2024
PDS	2D camera	BWe	Gp	Wan et al., 2024
PFR	2D camera	ID	Gp	Wada et al., 2013
PFR	2D camera	ID	Gp	Hansen et al., 2018
PFR	Smartphone	ID	Gp	Marsot et al., 2020
Pid	Computer vision	Dm, TBW	Pi	Ahrendt et al., 2011
Pid	2D camera	TBW	Gp	Cowton et al., 2019
Pid	2D camera	TBW	Gp	van der Zande et al., 2021
Tm	2D camera	MAi	Pi	Viazzi et al., 2014
Tm	GoPro	Lai	Fp	Gronskyte et al., 2015
Tm	2D camera	TBW	Gp	Nilsson et al., 2015
Tm	GoPro	LAi	Fp	Gronskyte et al., 2016
Tm	2D camera	DD	Gp	Martínez-Avilés et al., 2017
Tm	3D camera	TBW	Gp	Matthews et al., 2017
Tm	2D camera	DD	Wild boar	Fernández-Carrión et al., 2020
Tm	2D camera	TBW	Gp	Tu et al., 2024
Tp	3D camera	Tb	Gp	D'Eath et al., 2018
WPL	CCTV camera	LAi	M	Lind et al., 2005
WPL	2D camera	LAi	So	Grégoire et al., 2013
WPL	2D camera	LAi	Boars	Kongsro, 2013
WPL	Depth images	LAi	Gp	Stavarakakis et al., 2015b
WPL	3D camera	LAi	So	Stavarakakis et al., 2015a
WPL	2D camera	LAi	So	de Paula et al., 2024

¹Studies are sorted alphabetically by type of data, and then chronologically. Please note that abbreviations are sorted in alphabetical order within each footnote number.

²BC = behaviors classification; Bt = body temperature; Cl = claw lesion; Dv = drink nipple visits; FoT = feeder occupation time; It = image tracking; Le = ear and tail lesions; LI = lung lesions; LP = lying patterns; MAi = monitor aggressive interactions; Pa = pig area; PaW = pig area and weight; Pd = pig dimensions; Pdet = posture detection; PDS = pig dimensions and shape; PFR = pig face recognition; Pid = pig identification; Tm = tracking movements; Tp = tail posture; WPL = walking pattern and locomotion.

³CCD = charge-coupled device; CCTV = closed-circuit television; IRt = infrared thermography; MCDS = mobile claw scoring device.

⁴BCSd = assessing BCS; Bm = body measurements; BSe = body size estimation; BWe = BW estimation; CHe = claw health evaluation; CTC = classify thermal comfort; DB = drinking behavior; DD = disease detection; De = detect estrus; Dm = detect movement; EPO = estimation of parturition onset; FB = feeding behavior; FI = feed intake; Gd = group division; GRd = growth rate determination; ID = identification; LAi = locomotion abnormalities identification; LWd = live weight determination; Ma = monitor activity; MAi = monitor aggressive interactions; MB = maternal behavior; Me = mass estimation; Mip = monitor individual pigs; Pb = postural behaviors; PS = piglet survival; Tb = time budgets; TBW = tracking behavior and welfare; Tm = tracking movements; WA = welfare assessment.

⁵Fp = finishing pigs; Gp = growing pigs; M = minipigs; Np = nursery pigs; Pi = piglets; So = sows.

and U-Net architectures, the system achieved accuracies of 0.90 (lateral) and 0.72 (dorsal), demonstrating the feasibility of posture-based lameness detection. The study also emphasized the importance of curated image repositories, while noting the challenges of manual labeling and the need for balanced data sets across locomotion scores. The possibility of obtaining both lateral and dorsal models simultaneously was considered particularly promising for group-housed sows, where camera occlusion or damage are recurrent issues.

Tail posture has been investigated as an indirect indicator of welfare and lameness. D'Eath et al. (2021) demonstrated that deviations from expected age-related tail posture patterns were associated not only with tail biting but also with lameness and other health issues. These findings suggest that automated tail posture monitoring could serve as a valuable early-warning system.

In addition to welfare and climate monitoring, image analysis techniques have been extensively applied to assess growth performance, a critical parameter in pig farming (Schofield, 1990; Brandl and Jørgensen, 1996; Shi et al., 2016; Cang et al., 2019). Body condition scoring has also benefited from advancements in imaging technology. Traditional BCS is subjective and labor intensive, whereas vision-based systems provide more objective and repeatable assessments. He et al. (2023) developed an automatic algorithm for pig BCS based on an improved YOLOX network. Using more than 21,000 images from 1,674 pigs, the authors integrated an attention mechanism and a dynamic loss weight optimizer to enhance prediction accuracy. The model achieved an average precision of 80% on an independent test set, with only a slight performance drop when deployed on a Jetson NX platform, while maintaining real-time inference speed. These results indicate the feasibility of applying automated BCS systems in practical pig production. These approaches are particularly relevant in breeding herds, where maintaining optimal body condition is crucial for reproductive performance and herd sustainability. Body measurements derived from these systems can detect variations in animal sizes and shapes (Guo et al., 2017; Condotta et al., 2018; Lu et al., 2018b; Wang et al., 2018; Win et al., 2021) and estimate live weights with high precision while reducing human labor as well as risks and stressors for personnel and animals. Accurate live weight measurement is essential for assessing growth, uniformity, feed conversion efficiency, and disease occurrence, all of which are critical for evaluating pig health and productivity (Wongsriworaphon et al., 2015).

Last, image-based systems have also been tested for the automatic detection of other behaviors such as mounting (Nasirahmadi et al., 2016), further underlining the broad versatility of camera technologies in swine production. Taken together, the integration of locomotion analysis, automated claw and leg scoring, body and tail posture monitoring, and body condition assessment illustrates the rapid progress of camera-based PLF technologies. By providing objective, continuous, and scalable data, these systems en-

hance disease detection, welfare monitoring, management efficiency, and long-term genetic improvement in intensive pig production.

Image recognition also proved effective in detecting aggressive behaviors in weaned piglets, with detection accuracies of 89.0%, a sensitivity of 88.7%, and a specificity of 89.3% (Viazzi et al., 2014). Furthermore, Camerlink et al. (2018) analyzed facial metrics and expressions in 38 pigs to infer emotional states linked to aggression and fear during confrontations. Metrics such as ear angle, the snout length-to-height ratio, and eye modifications showed clear correlations with negative emotional contexts. One of the most promising applications of image analysis is facial recognition in pigs, which enables individual identification without the need for invasive markers. Wada et al. (2013) achieved 77% accuracy by analyzing entire facial regions and 97% accuracy by focusing solely on the ocular area. Similarly, Hansen et al. (2018) employed high-speed digital photography and neural networks to differentiate pigs with 96.7% precision.

Thermal imaging is a contactless, noninvasive technology that employs specialized cameras to capture images of the infrared radiation emitted by objects (Reza et al., 2024). The resulting thermogram depicts the apparent temperature distribution across the surface by detecting the intensity of incident radiation, rather than directly measuring surface temperature (Vollmer and Möllmann, 2017). This approach is particularly valuable for the rapid assessment of body temperature (Reza et al., 2024), a key physiological indicator of pig health and an essential parameter for disease diagnosis and health monitoring (Sadeghi et al., 2023; Xie et al., 2023). Nonetheless, despite its importance, conventional rectal temperature measurement is labor intensive and time consuming and can induce stress responses in pigs (Zhang et al., 2019b). Such stress may cause a rapid increase in rectal temperature, undermining the validity of the measurement (Godyn and Herbut, 2017). For this reason, several studies have explored thermal imaging as an alternative method for assessing pig body temperature. Because thermal imaging measures surface rather than core temperature, discrepancies exist between skin or s.c. temperature and rectal temperature (Xiong et al., 2023), mostly due to external conditions (e.g., wet or hairy skin, heat sources, vasodilation), which may affect the reliability of the measurement (Reza et al., 2024). Nevertheless, significant positive correlations have been reported (Zhang, 2015), suggesting that predictive models are needed to reliably infer rectal temperature from thermal data (Xiong et al., 2018). Among different anatomical sites, the ear and, in particular, the ear base have been identified as the most reliable regions for thermal imaging, because their temperature closely reflects pigs' core temperature (Lu et al., 2018a; Zhang et al., 2019b; Schmitt and O'Driscoll, 2021; Stukelj et al., 2022).

Thermal imaging has shown potential for multiple applications in swine production. By measuring infrared radiation emitted from pigs' bodies, thermography can identify

elevated body temperatures that may indicate illnesses such as fever or respiratory infections. For example, thermal imaging of groups of piglets has been used to detect febrile responses to vaccination, even when only 10% of the group was vaccinated (Cook et al., 2015). Similarly, Loughmiller et al. (2001) applied thermography to identify febrile responses following inoculation with *Actinobacillus pleuropneumoniae*. Xiong et al. (2023) combined infrared thermography with machine learning models to estimate body temperature for regulating supplemental heating devices, thereby reducing mortality within the first day of life. Siewert et al. (2014) demonstrated that thermal imaging can enable early detection of pigs with elevated body temperatures ($>39.5^{\circ}\text{C}$), achieving approximately 86% sensitivity and 85% specificity. Kammersgaard et al. (2013) also explored the use of thermal imaging to noninvasively estimate body temperature and assess the thermal condition of newborn piglets. More recently, Jia et al. (2020) extracted surface temperatures from the eye, ear base, back, and vulva and combined these with ambient temperature and humidity data to develop machine learning models for predicting the core body temperature of nonpregnant sows. Gorczyca et al. (2018) similarly employed thermography and machine learning approaches to estimate core, skin, and hair-coat temperatures in 5-d-old piglets. Beyond fever detection, thermal imaging can identify hypothermia and stress-related thermal changes, such as reduced peripheral temperature during systemic stress (Nääs et al., 2014). Furthermore, correlations between ear temperature and cortisol levels confirm the association between thermal variations and stress responses (Warriss et al., 2006).

Jorquera-Chavez et al. (2020) integrated computer-based methods with thermal and conventional imaging to monitor eye and ear-base temperatures, heart rate, and respiration rate. They observed distinct differences between healthy and sick pigs. Although not diagnostic for specific conditions, thermal imaging can provide insights into surface blood flow, reflecting physiological or pain states. For example, Amezcua et al. (2014) used thermal images of legs as a sensitive and noninvasive tool to distinguish between lame and nonlame sows. Despite variability in mean temperature, the study highlighted the effectiveness of infrared thermography in lameness detection.

Reproductive monitoring represents another application of this technology. Infrared thermography has been used to detect changes in vulvar temperature of sows and gilts during the periovulatory period (Scolari et al., 2011; Sykes et al., 2012; Simões et al., 2014). A significant decrease in vulvar temperature before ovulation was observed, although it remains unclear whether temperature peaks occur exclusively in the vulvar region or as a secondary response to systemic body temperature changes. During estrus, increased blood flow through the internal pudendal artery, driven by rising estradiol levels from developing follicles, elevates vulvar surface temperature (Frandsen et al., 2009). Anatomically, the gilt's vulva is more promi-

nent than in other livestock species and less obscured by the tail, making surface temperature changes easier to detect. Based on this principle, Sykes et al. (2012) applied thermography to distinguish between estrus and diestrus phases of the porcine estrous cycle. Similarly, Scolari et al. (2011) reported that thermographic imaging could detect an increase followed by a decrease in vulvar skin temperature several hours before ovulation, whereas gluteal skin temperature remained relatively constant, reflecting stable core temperature. Thus, vulvar thermography may represent a valuable tool for predicting ovulation, particularly when combined with conventional estrus detection methods such as boar exposure.

Additional evidence supports the use of infrared thermography in farrowing management. Monitoring auricular skin temperatures of sows 1 wk before expected farrowing may provide a baseline temperature for each sow, from which an increase of at least 2°C can be indicative of parturition within the following 8 to 16 h (Gulliksen et al., 2023). This approach may improve farrowing management by enabling more efficient human assistance and enhancing both sow and piglet welfare. Likewise, infrared thermography has shown value in early detection of shoulder sores, with Staveley et al. (2022) reporting an 88% detection rate up to 7 d before sore eruption, allowing early intervention. Although additional labor is required for regular inspection, this method could be integrated into routine sow monitoring. The availability of smaller, cost-effective, smartphone-compatible thermal cameras further supports the practical implementation of this technology.

Beyond reproduction and disease detection, infrared thermography has been employed for inflammation monitoring (Menzel et al., 2014), ovulation tracking (Luño et al., 2013; Simões et al., 2014), behavioral assessment (Cook et al., 2018), and growth evaluation (Caldara et al., 2014). Schmidt et al. (2013) and Barbieri et al. (2021) noted that relatively few studies have focused on pigs, and even fewer have systematically validated infrared thermography as a tool for identifying body temperature increases. The integration of thermal imaging with sensor technologies and advanced analytics may overcome these limitations, providing more objective and reliable data than visual assessments alone.

The potential of thermal imaging also extends to pre-slaughter monitoring. Weschenfelder et al. (2013) demonstrated that temperature changes detected through thermal imaging can reflect physiological status and predict pork quality variation under commercial conditions. Unlike other real-time assessment techniques, this technology provides a restraint-free and noninvasive method for evaluating stress-related physiological responses in live pigs immediately before slaughter. Such measurements may enable early postmortem segregation of carcasses based on body temperature and help processors minimize meat quality losses associated with elevated muscle temperature, which accelerates pH decline. This can be achieved through modified postmortem carcass handling

strategies, such as faster carcass cooling (Edwards et al., 2010).

Moreover, de Fátima Araújo Alves et al. (2024) highlighted the utility of infrared thermography for detecting heat stress in pigs, demonstrating that surface temperature analysis combined with classification models can facilitate early identification of heat stress conditions. Such tools may serve as diagnostic aids for veterinarians, supporting timely preventive measures to mitigate the adverse effects of heat stress, which include impaired growth, reduced productivity, and increased health risks.

Despite these promising applications, it is essential to recognize the limitations of thermal imaging in practice. As highlighted by Hajdinjak et al. (2025), measurement uncertainty can be significant because of factors such as hair coverage, dirt, moisture, background radiation, and the limited precision of many infrared cameras. Even under optimal conditions, accuracy is generally no better than $\pm 1^\circ\text{C}$, provided the device is calibrated to the ITS-90 reference temperature scale and appropriate corrections are applied. In typical scenarios, however, the precision of infrared thermography cameras is closer to $\pm 2^\circ\text{C}$, which is insufficient for reliable clinical measurements. The use of low-precision infrared thermography devices without adherence to standardized measurement protocols represents a major limitation in many earlier studies. To date, the development of camera-based systems for pigs has remained at the experimental stage, with no commercial systems yet available.

Slaughterhouses are a pivotal point of observation for evaluating lifelong welfare conditions (EFSA Panel on Animal Health and Welfare et al., 2022). Automated image analysis systems have been explored for identifying lesions on carcasses, such as tail injuries, ear lesions, and lung pathologies (Ferri et al., 2024). These indicators are key for assessing issues such as tail biting, aggression, or respiratory health problems during the animal's lifetime (EFSA Panel on Animal Health and Welfare et al., 2022). For example, technologies leveraging high-resolution imaging and machine learning algorithms can detect tail injuries with precision, facilitating the evaluation of housing and management practices (Blömke et al., 2020). Similarly, lung lesion detection in pig carcasses via imaging has been used to assess the prevalence of pneumonia or pleurisy, providing insights into respiratory health and ventilation quality inside barns (Bonicelli et al., 2021). Although the European Food Safety Authority (EFSA Panel on Animal Health and Welfare et al., 2022) strongly supports the implementation of such technologies to enhance animal welfare monitoring, no single preferential system has been indicated. This highlights the need for further research and standardization to integrate these tools effectively into routine slaughterhouse operations.

Overall, for camera-based monitoring, the integration of image analysis with AI and machine learning was already suggested in 2015 as a technology capable of revolutionizing pig farming (Nilsson et al., 2015). Since then,

significant progress has been made, with recent studies demonstrating its application in automated monitoring of health, behavior, and productivity (Wang et al., 2022). Systems driven by AI could enhance the robustness and reliability of these tools, enabling them to perform effectively in complex environments with varying lighting conditions and multianimal interactions. Combining image-based technologies with Internet of Things devices and existing farm management platforms offers a holistic approach to monitoring animal health, welfare, and productivity. Additional future developments may focus on applications such as emotional state monitoring via facial expression recognition, improved tracking of feeding and drinking behavior (Kashiha et al., 2013a; Yang et al., 2018; Alameer et al., 2020), and multispectral imaging for identifying physiological changes linked to inflammation or stress (Kongsro, 2013), as well as on the detection and benchmarking of carcass lesions at slaughter. Over time, these technologies will play a crucial role in improving farm efficiency, ensuring animal welfare, and advancing the sustainability of pig production systems.

Sound-Based Monitoring. Listening to a herd or group can reveal communication patterns and signs of aggression or illness, providing valuable insights into the herd's overall well-being. Sound analysis has distinct technical advantages over other monitoring methods. Microphones can capture audio data regardless of environmental conditions such as temperature, humidity, or dust, and they function properly not only when illumination is on, but also in darkness. Cameras and microphones provide complementary information, with cameras particularly suited for parameters such as weight estimation and activity. In contrast, sound analysis excels at detecting respiratory symptoms, such as coughing. From a practical standpoint, however, cameras often require regular maintenance, such as lens cleaning, and wearable sensors may need frequent battery recharging. In this regard, sound analysis represents an efficient and elegant technique for acquiring meaningful data with minimal operational challenges. Microphones also function effectively in large spaces, whereas cameras are limited by their field of view. Overall, sound analysis is a noninvasive, low-cost method for continuously and automatically monitoring specific health-related variables (Van Hirtum et al., 1999). By analyzing animal sounds, including vocal and nonvocal signals, this approach provides valuable insights into physiological states, behavioral patterns, and overall welfare.

Recent advancements in machine learning have significantly enhanced the ability to process and interpret complex sound patterns, broadening the applications of sound analysis in livestock management. For example, microphones have demonstrated over 73% accuracy in assessing and classifying vocalizations across 8 out of 9 validation studies (Gómez et al., 2021). One sound-analysis algorithm achieved 98% accuracy in distinguishing stress vocalizations associated with pain, and accuracy rates for detecting vocalizations related to hunger, thirst, or ther-

mal discomfort ranged from 69% to 71% (da Silva et al., 2019).

Coughing in pigs is one of the most studied applications of sound analysis, because it often indicates respiratory disease or poor environmental conditions such as high levels of dust or ammonia. Specialized algorithms can detect and quantify coughing sounds, enabling the monitoring of cumulative cough counts within a group (Chedad et al., 2001; Exadaktylos et al., 2008; Silva et al., 2009). Studies (Wang et al., 2019; Shen et al., 2022; Chae et al., 2024) have reported confidence intervals of 95% for detecting coughing at the barn level, with accuracy rates between 73% and 93% for correctly identifying sick groups based on coughing sounds. Advanced software has also been developed to distinguish between dry and productive coughs, enabling farmers to identify respiratory issues early and reduce reliance on antibiotics (Silva et al., 2009).

Additionally, identifying stress and pain-related vocalizations (such as those occurring during aggression and fighting events or during tail biting) has promising applications for assessing welfare traits. Vocalizations linked to pain are often more reliably identified than those linked to hunger or thermal discomfort, but expanding the catalog of vocal signals analyzed could improve assessments of both negative welfare aspects (e.g., stress and disease) and positive indicators (such as social bonding and contentment).

Sound analysis has also been applied to detect piglets at risk of being crushed by sows. In a German study (Manteuffel et al., 2017), stress-related vocalizations associated with crushing events were less frequent than other stress-related sounds. By incorporating contextual parameters such as piglet age and the sow's postural behavior, researchers achieved specificity and sensitivity of 95% and 70%, respectively, in detecting crushing events (Manteuffel et al., 2017). Key studies on the application of sound analysis in swine farming are summarized in Table 2. This summary underscores the breadth of research conducted and the promising role of sound analysis in enhancing the monitoring of pig health and welfare. In addition to detecting health problems and monitoring air quality, one of the most intriguing applications of sound analysis is assessing animal welfare. The automatic analysis of stress vocalizations in pigs has yielded promising results in identifying stressful situations. Schön et al. (2004) developed a system called STREmodo (Stress Monitor and Documentation Unit), that combines linear prediction coding with an artificial neural network to detect stress-related pig vocalizations from audio recordings made with microphones. High-frequency squeals were easily distinguished from nonstress-related vocalizations. Vandermeulen et al. (2015) further characterized stress vocalizations by analyzing their duration and spectral properties to develop an algorithm that automatically detects squeals. Although these studies did not use cameras alongside microphones, preventing the determination of squeal causes, they demonstrated that pig vocalizations can be clearly identified

in sound data, allowing for automatic monitoring of stress-related events. Hesecker et al. (2024) showed that adding video cameras to sound analysis systems can help identify the origin of squeals, distinguishing aggressive individuals from nonaggressive ones. This additional layer of data enabled the early identification of aggressive pigs up to 9 d before farm staff could detect them through visual inspection. As a result, removing aggressive pigs from pens earlier significantly reduced the number of injured pigs with tail lesions.

Overall, sound-based monitoring systems can detect early signs of respiratory problems, enabling timely interventions and addressing contributing factors such as air quality and climatic conditions. Future research should prioritize expanding the catalog of vocal signals analyzed to include positive welfare indicators, enhancing the ability to comprehensively assess animal well-being. Ongoing advancements in bioacoustics and machine learning, when integrated with other PLF tools such as environmental sensors and video monitoring systems, have the potential to provide a comprehensive and holistic approach to animal monitoring (van Erp-van der Kooij et al., 2023).

Activity-Based Monitoring. Microelectromechanical devices equipped with inertial measurement units (IMU) have revolutionized the study of animal behavior, as electronics have become smaller and more affordable over the past 2 decades (Cade et al., 2021). These wearable tags enable fine-scale determination of behavior without direct observation, which is particularly valuable in intensive housing systems where visual monitoring can be limited by herd size or facility design. Inertial measurement units, typically consisting of accelerometers and gyroscopes, can be embedded in wearable devices or integrated into the housing environment (e.g., pressure mats or vibration sensors) to quantify movement and activity patterns in pigs (Try and Gebhard, 2022; Pan et al., 2023). Motion-based devices offer several advantages, including their low cost, small size, light weight, low power consumption, and potential for large-scale application (Xuan et al., 2024).

Accelerometers, which measure linear acceleration, are widely used as motion detectors (DeVaul and Dunn, 2001) and for body position and posture sensing (Foerster et al., 1999). Because they respond to acceleration due to movement and gravitational forces, wearable accelerometers with wireless interfaces show strong potential for remote behavioral monitoring. When combined with gyroscopes that measure angular velocity, accelerometers form the core of IMU and directly determine the accuracy of motion-based monitoring systems (Mobbs et al., 2022). Key studies on activity-based technologies in swine production are summarized in Table 3.

These technologies enable continuous and objective assessment of behaviors such as standing, lying, walking, feeding, changes of posture, and even social interactions (Cornou and Lundbye-Christensen, 2008). In swine production, IMU-based systems have been deployed in wearable configurations (Chapa et al., 2020). Wearable devices

Table 2. Overview of main studies on sound analysis in pigs¹

Type of data ²	Application	Animal category ³	Reference
AA	Body size	Pi	Garcia et al., 2016
CM	Air quality and health status	Gp	Chedad et al., 2001
CM	Identify respiratory infection	Pi	Aerts et al., 2005
CM	Identify health problems	Pi	Exadaktylos et al., 2008
CM	Identify respiratory infection	Gp	Ferrari et al., 2008
CM	Identify health problems	Fap	Guarino et al., 2008
CM	Identify respiratory infection	Fap	Silva et al., 2009
CM	Detection of wasting disease	Gp	Chung et al., 2013
CM	Air quality	Wp	Wang et al., 2019
GA	Emotional reactivity	Wp	Briefer et al., 2019
SM	Identify stressful situations	Gp	Vandermeulen et al., 2015
SM	Detecting tail biters	Wp	Heseker et al., 2024
VA	Pain detection	Pi	Weary et al., 1998
VA	Pain detection	Gp	Marx et al., 2003
VA	Thermal discomfort	Fap	Hillmann et al., 2004
VA	Identify emotional states	Pi	Schön et al., 2004
VA	Identify stressful situations	Pi	von Borell et al., 2009
VA	Heat stress	Pi	Ferrari et al., 2013
VA	Emotional reactivity	Gp	Leliveld et al., 2017
VA	Detect piglet crushing	Pi	Manteuffel et al., 2017
VA	Detect piglet crushing	Pi	Chapel et al., 2018
VA	Identify sex, age, and distress conditions	Gp	da Silva Cordeiro et al., 2018
VA	Identify stressful condition	Pi	da Silva et al., 2019
VA	Respiratory disease and aggressive behaviors	Gp	Hong et al., 2020

¹Studies are sorted alphabetically by type of data, and then chronologically. Please note that abbreviations are sorted in alphabetical order within each footnote number.

²AA = acoustic allometry; CM = cough monitoring; GA = grunts analysis; SM = scream monitoring; VA = vocalization analysis.

³Fap = fattening pigs; Gp = growing pigs; Pi = piglets; Wp = weaner pigs.

(such as ear tags, leg tags, or collar-mounted accelerometers) enable the precise collection of activity data at the individual level across several species (Main et al., 2000; Cornou et al., 2011; Scheel et al., 2017). According to Traulsen et al. (2016), ear sensors coupled with a receiver system are an objective and user-friendly method to detect activity changes, with applicability beyond experimental farms. Differences in activity indices derived from positioning data have revealed altered movement in lame sows. However, daily acceleration values were less reliable than changes in movement behavior for detecting lameness, and further validation with larger data sets was recommended (Traulsen et al., 2016).

Pan et al. (2023) developed an ear-tag IMU combined with deep learning algorithms to monitor pig behavior, demonstrating the feasibility of automated activity tracking. Similarly, accelerometers have been used to classify postures and detect changes in movement associated with health status or reproductive events (Zhang et al., 2022; Glencorse et al., 2025). Real-time monitoring of prenatal activity patterns during parturition has also been achieved with 3-axis accelerometers (Ringgenberg et al., 2010).

Despite these advances, direct adoption of wearable technologies from human healthcare (e.g., smartwatches, fitness trackers) into swine production remains impractical. Human wearables are cost prohibitive (typically >\$50 per device) and anatomically unsuitable for pigs. Adhesive skin-worn sensors are ineffective on hairy animals, and commercial smart collars designed for cattle or companion animals are too heavy, expensive, or easily damaged by pigs' inquisitive and chewing attitudes. Cornou et al. (2011) applied accelerometers to sow behavior monitoring and classified 5 types of activity (high activity, medium activity, lateral lying on the left or right side, and ventral lying), achieving classification accuracies of 75% to 100% for activity types and 96% to 100% for broader activity categories. This approach, unlike infrared photocells or force sensors previously tested in farrowing crates (Erez and Hartsock, 1990; Oliviero et al., 2008), can be applied across different housing systems.

Depending on sensor placement and data processing, accelerometers can distinguish whether a sow is lying laterally (Cornou and Lundbye-Christensen, 2008, 2010; Ringgenberg et al., 2010; Escalante et al., 2013) and on

Table 3. Overview of main studies on motion-based technologies in pigs¹

Type of data ²	Application ³	Animal category ⁴	Reference
Am	BC	So	Cornou and Lundbye-Christensen, 2008
Am	BC	So	Cornou and Lundbye-Christensen, 2010
Am	BC	So	Cornou et al., 2011
Am	TBW	So	Marchioro et al., 2011
Am	EPO	So	Cornou and Lundbye-Christensen, 2012
Am	BC	So	Escalante et al., 2013
Am	EPO	So	Cornou and Kristensen, 2014
Am	DD	Pi	Ahmed et al., 2015
Am	TBW	So	Oczak et al., 2015
Am	TBW	Gp	Matthews et al., 2016
Am	LAI	So	Traulsen et al., 2016
Am	LAI	So	Scheel et al., 2017
Am	BC	So	Thompson et al., 2019
Am	Sq	Bo	Stravogianni et al., 2022
Am	TBW	Gp	Cheung et al., 2023
Am	TBW	So	Pan et al., 2023
Fs	EPO	So	Oliviero et al., 2008
Fs	LAI	So	Pluym et al., 2013
Htm	TBW	Gp	Pandey et al., 2021
PD	TBW	So	Huang et al., 2004
PD	LAI	So	Grégoire et al., 2013
PD	TBW	So	Oczak et al., 2016
PD	TBW	So	Thompson et al., 2016
PD	EPO	So	Knoll et al., 2024
Sd	LAI	So	Ringgenberg et al., 2010
Vd	TBW	So and Pi	Dong et al., 2023

¹Studies are sorted alphabetically by type of data, and then chronologically. Please note that abbreviations are sorted in alphabetical order within each footnote number.

²Am = acceleration measurements; Fs = force stance; Htm = head tilt and movement; PD = posture detection; Sd = stepping detection; Vd = vibration data.

³BC = behaviors classification; DD = disease detection; EPO = estimation of parturition onset; LAI = locomotion abnormalities identification; Sq = sperm quality; TBW = tracking behavior and welfare.

⁴Bo = boar; Gp = growing pigs; Pi = piglets; So = sows.

which side (Thompson et al., 2016, 2019) or sternally (Cornou and Lundbye-Christensen, 2008, 2010; Ringgenberg et al., 2010; Cornou et al., 2011; Escalante et al., 2013; Thompson et al., 2016, 2019). They can also differentiate standing from walking (Thompson et al., 2019), detect sitting (Ringgenberg et al., 2010; Thompson et al., 2019), depict postural transitions (Thompson et al., 2016, 2019), and identify rooting behavior (Cornou and Lundbye-Christensen, 2008, 2010; Escalante et al., 2013).

However, limitations remain. Discrimination between standing and sternal lying using back- or neck-mounted accelerometers is often unreliable (Thompson et al., 2019). Sitting is also difficult to classify: Ringgenberg et al. (2010) achieved only 37% accuracy, Thompson et al. (2019) could not robustly separate sitting from sternal lying, and Cornou et al. (2011) merged these into “medium activity.” Yet, distinguishing these postures is critical, because up to 27% of piglet crushing events occur while sows are sitting

(Vieuille et al., 2003). Improved precision may be achieved by combining multiple sensors, e.g., leg- and neck-mounted accelerometers, which enhance detection of posture transitions (Brouwers et al., 2023; Simmler and Brouwers, 2024). However, at present, these kinds of sensors remain (largely) underused in pigs because of their anatomic conformation. Thompson et al. (2016) proposed a framework for classifying sow postures and posture transitions, enabling large-scale continuous assessment. Around farrowing, such monitoring is particularly relevant, as lying and rolling transitions are major risk factors for piglet crushing (Wechsler and Hegglin, 1997; Marchant et al., 2001). Tri-axial accelerometers have been successfully applied to detect estrus (Cornou, 2006), posture states (Cornou and Lundbye-Christensen, 2008), farrowing activity (Oczak et al., 2015), and the onset of parturition (Cornou and Lundbye-Christensen, 2012). More recent work has automated posture transition detection and linked maternal behavior

with piglet survival (Thompson et al., 2019; Knoll et al., 2024).

Feeding-related behaviors have been less frequently investigated using these sensors. Fleming et al. (2018) used accelerometers on piglets fitted with neck collars to study the effects of diet and circadian rhythms. Using the Actiware software, activity thresholds were determined to classify sleep and awake states, and the results were validated against manual observations. Although diet had no significant effect, greater activity was recorded during the day, and more sleep was recorded at night. Such simple, reproducible methods may still provide valuable evidence of welfare issues (Weary et al., 2009; Matthews et al., 2016, 2017).

Accelerometer-equipped ear tags have also proven helpful for health surveillance. For example, Ahmed et al. (2016) tested a ZigBee-based wireless system in piglets experimentally infected with *Salmonella enteritidis* or *Escherichia coli*. Altered axial movements were detected relative to controls, reflecting reduced feed intake and discomfort associated with infection. Movements along the X-, Y-, and Z-axes varied across the first 5 d after infection, with increased vertical movement (Z-axis) during the first 3 d, likely due to gastrointestinal distress, followed by reduced activity. Ringgenberg et al. (2010) validated 2 accelerometers, placing one on a rear leg and another on the sow's back, to quantify hind limb steps during feeding episodes. Although recognition was generally reliable, limitations included short memory capacity (maximum of 1 h 50 min of recording at 0.1-s intervals) and occasional false positives or negatives due to small steps, body shaking, or device misalignment. Despite these drawbacks, accelerometer-based step detection shows promise for locomotion and lameness studies in group-housed sows. Similarly, ear tag accelerometers combined with temperature sensors have identified infections 1 to 3 d before conventional sampling (Martínez-Avilés et al., 2017).

Beyond accelerometers, alternative motion-based technologies have also been tested. Pandey et al. (2021) integrated electronic sensors into ear tags for activity tracking, and pressure mats provided objective gait analysis for early lameness detection (Meijer et al., 2014). Plum et al. (2013) developed SowSIS, a transportable detection system combining force plate and image processing data, which distinguished lame from sound sows in a pilot study. Similarly, Oliviero et al. (2008) demonstrated the potential of photocell and force sensor systems to monitor sow activity in farrowing crates and predict parturition onset.

Nevertheless, the widespread adoption of wearable IMU in commercial pig production remains constrained by device costs, durability, and welfare concerns, because wearables may cause discomfort or stress and can also be removed or damaged by the animals themselves (Maselyne et al., 2014; Dong et al., 2023). To overcome these challenges, noninvasive structural sensors (such as vibration detectors or geophones embedded in flooring) have been explored (Try and Gebhard, 2022). These systems capture

mechanical vibrations from pig movements and provide group-level information on activity cycles, disturbances, and environmental responses, while reducing handling stress. However, they offer lower resolution at the individual level compared with wearables.

Overall, motion-based technologies offer valuable opportunities for monitoring swine behavior, health, and welfare (Chapa et al., 2020). Their ability to detect early signs of illness, monitor reproductive status, and characterize responses to environmental stressors highlights their relevance for PLF. Future applications will depend on balancing data resolution with practicality and welfare and on integrating activity-based measures with other PLF technologies to support decision-making in intensive pig production.

Radio-Frequency Identification. The first step to collect individual data for health and production monitoring is the accurate identification of each pig. Radio-frequency identification (**RFID**) tags can be used for this purpose. Radio-frequency identification tags are small devices, typically embedded in ear tags, that store and transmit identification data about the animal, enabling quick and accurate identification. Radio-frequency identification systems have been extensively applied to measure feeding and drinking patterns of individual pigs, including both the occurrence and duration of these activities. The system typically consists of an RFID transponder (ear tag) and an RFID antenna or receiver located at feeders or drinkers. When a tagged pig is in proximity to the receiver, the system records its presence, providing detailed data about individual activity (Reiners et al., 2009; Faltys et al., 2014; Maselyne et al., 2014, 2016a, 2016b; Gertheiss et al., 2015; Adrion et al., 2018; Cross et al., 2018).

A well-established application of RFID technology in intensive swine production is the electronic feeding station, which uses RFID-based identification to regulate feed distribution and simultaneously monitor individual feed intake (Young and Lawrence, 1994; Reiners et al., 2009). Electronic feeding stations are among the most widely adopted PLF technologies on commercial farms, providing both nutritional management and welfare insights in group-housed swine (Paura and Jonkus, 2016). Given their relevance, electronic feeding station applications will be discussed in greater detail in the dedicated section in the following.

There are 2 primary types of RFID technology used in pig farming: low-frequency and ultra-high-frequency (**UHF-RFID**) systems. Low-frequency RFID systems are highly effective for monitoring behaviors such as feeding and drinking, but they are limited by their short communication range and inability to distinguish between multiple transponders within a single receiver's range. Alternatively, combining a multiplexer with UHF-RFID technology enables accurate identification of individual pigs within a group (Maselyne et al., 2014). Combining RFID with additional sensors can further enhance monitoring accuracy. For example, water flow sensors integrated with RFID

Table 4. Overview of main studies on radio-frequency identification technologies in pigs¹

Type of data	Application	Animal category ²	Reference
Drinking times	Drinking behavior	FP	Maselyne et al., 2016a
Feeder visits	Localization	Pi	Reiners et al., 2009
Feeder visits	Feeding behavior	Gp	Adrion et al., 2018
Feeding patterns	Feed intake and behavior	Gp	Faltys et al., 2014
Feeding patterns	Feeding behavior	FP	Maselyne et al., 2014
Feeding patterns	Feeding behavior	Gp	Maselyne et al., 2016b
Feeding patterns	Feeding behavior	FP	Cross et al., 2018
Feeding times	Feeding behavior	Fap	Gertheiss et al., 2015
Position markers	Localization in farm	Gp	Porto et al., 2012

¹Studies are sorted alphabetically by type of data, and then chronologically.

²Fap = fattening pigs; FP = finishing pigs; Gp = growing pigs; Pi = piglets.

have shown greater precision in measuring drinking behavior than water flow sensors alone (Maselyne et al., 2016a). However, the system's accuracy depends on the position and orientation of the RFID tags relative to the receivers (Maselyne et al., 2014). Measuring location-based behaviors, such as daily activity budgets, is restricted by the short communication range between the transponder and the antenna or receiver, a limitation due to the low power source of RFID tags. Some limitations of low-frequency RFID systems could be overcome by UHF-RFID systems, which can identify multiple animals over greater distances (3–10 m). However, these tags are more prone to interference, which can result in false readings (Matthews et al., 2017; Benjamin and Yik, 2019).

The use of RFID technology is not without challenges. Tags may be lost, their application can cause stress and pain to the animals, and ear tags must often be retrieved at slaughter, adding a further step (Benjamin and Yik, 2019). However, the detailed, real-time data provided by RFID systems make them invaluable for early detection of feeding or drinking abnormalities, enabling timely interventions. A summary of key studies on the application of RFID technology in swine farming is presented in Table 4.

Electronic Feeding Stations. Electronic feeding stations (EFS), most commonly implemented for sows kept in groups (Jensen et al., 1995), are among the most established PLF tools in commercial swine production (Young and Lawrence, 1994; Faltys et al., 2014). The prototypes were introduced during the early 1980s (Jensen et al., 1995; Remience et al., 2008), and since then the technology has become increasingly widespread, with adaptations for finishing pigs (Hoy et al., 2012; Paura and Jonkus, 2016), growing pigs (Bruininx et al., 2001; Munsterhjelm et al., 2015; Andretta et al., 2016), and even boars (Wal-lenbeck and Keeling, 2013).

Electronic feeding stations rely on RFID-based individual identification to dispense rationed feed to group-housed

pigs while simultaneously recording detailed data on feed intake and eating bouts (Young and Lawrence, 1994; Reiners et al., 2009). Core components typically include a protected single-animal feeding stall with an RFID antenna, a controlled drop or auger feeder linked to a feeding algorithm, and software for data storage and alerts. When a pig enters the stall, the RFID antenna detects the ear tag transponder as the animal places its head inside the trough. A predetermined feed ration is dispensed while the entrance gate remains locked. Once feeding ceases, the exit gate opens to release the pig, and the entrance gate unlocks for the following individual. Data typically collected include pig identification number, date, feed weight at entry and exit, entry and exit times (Casey et al., 2005), and, in some cases, BW (Slader and Gregory, 1988; Jiao et al., 2014). From these records, key metrics are derived, such as feed intake per visit, occupation time per visit, and feeding rate (Jiao et al., 2016). Modern EFS also provide opportunities to automatically sort (through gates opening to different pens) animals for farrowing, treatments, vaccinations, or pregnancy checks, making them a helpful management tool (Olsson et al., 2011).

In practice, EFS bridge the gap between group housing and individual management. They enable parity- or body-condition-specific nutrition, support the early detection of deviations in feeding behavior indicative of health or welfare problems, and generate continuous data streams for analysis and decision support. For instance, Jensen et al. (1995) observed that group housing with EFS during gestation improved overall sow well-being compared with confinement housing, although welfare was transiently reduced at the time of grouping because of initial hierarchical fighting. This underscores the importance of the adaptation period when sows are first introduced into EFS pens. Similarly, Li et al. (2018) reported more lesions on the bodies of sows after mixing into EFS pens compared with before moving to the farrowing unit, regardless of

space allowance. However, they also found that vulva lesion scores were lower after mixing in EFS pens than before farrowing, suggesting complex dynamics in aggression and welfare outcomes.

Space allowance plays a key role in this context. Remience et al. (2008) showed that 3 m²/sow in dynamic groups reduced aggressive behavior and consecutive wounds compared with 2.25 m²/sow. Despite these clear welfare benefits, productivity was unaffected, and the implications for physiological stress still require further study. Social hierarchy is another critical factor (Manteuffel et al., 2010). Roy et al. (2019) found that dominant sows valued feeder access more than environmental enrichment, whereas subordinate sows exhibited more skin lesions and higher salivary cortisol concentrations, indicating increased stress in EFS systems for these animals.

Competition for feeder access remains a key challenge. Aggressive individuals are inadvertently rewarded with feed, thereby reinforcing aggression through operant conditioning (Olsson et al., 2011; Manteuffel et al., 2022). Low-ranking or younger sows are particularly vulnerable (Hoy et al., 2009). Restricted feeder access may also sustain oral motivation, leading to redirected behaviors such as chewing pen equipment or biting pen mates (Blanc et al., 2024). Durand et al. (2023) further noted that short-term dysfunction of one EFS unit in pens with 2 feeders had detrimental effects on sow behavior and welfare, although productivity was not compromised.

To address these issues, innovative solutions such as signal-feeding systems have been developed (Kirchner et al., 2012). Building on earlier research in growing pigs (Ernst et al., 2005; Manteuffel, 2009), this approach uses individual acoustic cues to grant feeder access (Manteuffel et al., 2011; Blanc et al., 2024). Sows are trained to approach only when their signal is emitted, reducing queuing and aggressive interactions. Training is typically consolidated within 12 to 38 d (Manteuffel et al., 2022). This strategy improves feeder accessibility for low-ranking sows, potentially supporting fetal development (Belkacemi et al., 2010) and decreasing stress during gestation. However, direct fertility and piglet health benefits remain to be confirmed.

Beyond immediate welfare management, EFS data offer opportunities for genetic improvement. Vargovic et al. (2021) demonstrated that feeding behavior traits recorded by electronic sow feeders (such as time spent eating, frequency of missed meals, or meal size), some of which are heritable, can be used to construct novel phenotypes. These findings highlight that even healthy, normal sows exhibit individual variability in appetite and feeding behavior, which could inform both management and breeding programs. However, most of the currently available EFS software does not consistently record cumulative low intakes or deviations from feed allocations, underscoring the need for system upgrades to exploit this potential fully.

Electronic feeding stations also serve as valuable monitoring tools. Wallenbeck and Keeling (2013) showed that

reduced feeding frequencies at the pen level predicted tail-biting outbreaks up to 9 wk before tail lesions appeared, and Ollagnier et al. (2023) used machine learning models with EFS data to identify early indicators of tail biting up to 35 d in advance. Such predictive capabilities may allow farmers to implement preventive strategies, such as increasing enrichment or analyzing risk factors, with clear welfare and economic benefits. Similarly, Funk et al. (2024) applied a low-frequency RFID system in grow-finish pigs to detect anomalous reductions in daily feeding time. Their model identified 56% of interventions needed on average 2.8 d earlier than treatment administration by caretakers, although false alarms remain a challenge.

Last, the use of EFS in farrowing barns is more controversial. Aparicio et al. (2024) reported that feeding individually housed sows via EFS during lactation impaired performance compared with conventional feeders, with sows losing BW, producing more milk with greater lactose concentration, and exhibiting reduced feed efficiency per kilogram of weaned piglets. This suggests that the benefits of EFS in gestation do not necessarily extend to the lactation period.

Overall, EFS represent a mature and widely applied PLF technology that combines precision feeding of the individual with continuous monitoring of feeding behavior. Their value can extend beyond feed delivery to encompass welfare management, genetic improvement, and early-warning systems for health and behavioral problems (Hall et al., 1999). However, challenges related to aggression, social hierarchy, software limitations, and housing context remain critical factors for successful implementation.

Dashboards for Data-Driven Management. In livestock farming operations, numerous sensors generate vast amounts of data (Neethirajan, 2024). However, to transform these data into actionable insights, they must be effectively processed and presented to farmers in an accessible format. To address this need, several companies have developed dashboards, i.e., digital platforms that aggregate, analyze, and visualize data from various sources. These tools are designed to provide farmers with a comprehensive overview of their operations, enabling them to make informed decisions for improved farm management (Dineva and Atanasova, 2022).

A dashboard serves as a centralized digital interface that collects and processes information in real time from multiple sources (such as environmental sensors, feed monitoring systems, and animal behavior tracking devices; Schönfeld et al., 2018). By visualizing these data, dashboards help farmers monitor critical variables such as temperature, humidity, feed intake, and animal weight. They also enable comparative analysis across different groups of animals, facilitating a better evaluation of farm management strategies and outcomes. Initially, dashboards were primarily used to visualize basic farm metrics, support routine operational management, and track actual versus projected growth rates. With advancements in software technologies, including machine learning and predictive analytics,

Table 5. A partial listing of commercially available (at the time of printing) dashboards for pig farming

Company	Dashboard	Website	Functions
Agrisyst	PigExpert	www.agrisyst.com	Animal data recording; health monitoring; feed management; herd analyses
Agritec	Porcitec	www.agritecsoft.com	Animal data recording; health monitoring; feed management; herd analyses
Agrosoft	WinPig.NET	www.agrosoft.eu	Feed management; herd analyses
Agrovision	PigVision	www.agrovision.com	Individual animal recording; drug record; feed management; herd analyses
Claas	Pig Farm Management	www.claas.com	Animal recognition; herd analyses; cross-farm comparisons
FarmResult	PigResult	www.farmresult.com	Individual animal recording; medicine registration; feed management; herd analyses
Follo3 software	Swine record keeping	www.agtech.folio3.com	Animal data recording; health monitoring; feed management; herd analyses
Garth Pig Practice Ltd.	Pig Focus	www.garthvet.co.uk	Herd analyses
Herdstar	GF Pro	www.herdstar.com	Production feed efficiencies; growth performance; marketing results
Hotraco	Prisma Farm Management	www.hotraco-agri.com	Climate management; feed and water management; animal weight
Isagri	Swine Management System	www.isagri.it	Animal data recording; health monitoring; feed management; herd analyses
Plan-a-head	Pig Software	www.planahead.co.za	Individual animal recording; drug record; herd analyses
Prüllage Systeme	Smart Farming Software	www.pruellage.de	Herd analyses

modern dashboards now offer advanced features such as anomaly detection, automated alerts, and trend forecasting (van Erp-van der Kooij and Rutter, 2020). These capabilities enable farmers to proactively address potential issues, optimize resource use, and improve animal welfare. Many smart barn controllers and PLF tools for specific functions already incorporate dashboard-like features, but their integration into holistic farm-level systems remains limited in swine production. Unlike the dairy sector, where PLF dashboards are increasingly validated (e.g., for monitoring performances, health, and environmental parameters, Nyamuryekung'e, 2024), such detailed monitoring in pig farming remains scarce. However, several commercially available dashboards for pig farming have been introduced to the market, offering features tailored to the needs of swine producers. Table 5 shows a nonexhaustive list of dashboards documented in the literature and technical reports. The table is intended as a list of examples rather than a comprehensive listing of all commercially available platforms.

These tools are not only practical but also strategic for managing pig farming operations. By enabling farmers to compare performance data across animal groups and evaluate the effects of various management decisions, dashboards facilitate improved supervision and coordination of farm activities. Furthermore, their ability to integrate

data from diverse systems supports a holistic approach to farm management, ensuring economic, environmental, and social sustainability.

Individual Versus Group Monitoring. As previously discussed, in modern pig farming, monitoring systems predominantly focus on groups or production units rather than individual animals (Norton et al., 2019). This is particularly evident in the management of weaned piglets and finishing pigs, where the majority of collected data pertain to group-level metrics (Nasirahmadi et al., 2015). Key parameters include feed and water intake, ADG, environmental conditions, and health-related indices, such as the cough index (Cornou and Kristensen, 2013). Because of the lack of individual animal identification in many systems, data collection on a per-animal basis remains challenging. As a result, health and production monitoring, as well as subsequent management decisions, are typically conducted at the group level. Diagnoses and treatments are therefore applied collectively, which may not always be optimal both in terms of diagnostic accuracy and drug use. Nevertheless, advancements in PLF technologies have introduced tools that enhance group-level monitoring while indirectly benefiting individual welfare (Cruz et al., 2022). For instance, continuous monitoring of feed and water intake patterns, acoustic surveillance to detect coughing frequency, and behavioral analysis using

video- or sensor-based systems provide insights into the overall health and performance of the group (Cornou and Kristensen, 2013). Detecting early signs of health disturbances (such as increases in coughing frequency, reduced feed or water intake, or deviations from typical activity patterns) allows for prompt intervention (Ferrari et al., 2008; Shen et al., 2022). Early detection not only minimizes the number of animals requiring treatment but also prevents disease outbreaks, reducing both health risks and economic losses at the farm level (Chae et al., 2024). For example, irregularities in group behavior or environmental conditions can serve as early indicators of respiratory issues, gastrointestinal disturbances, or heat stress (Pandey et al., 2021; Tu et al., 2024). These insights enable targeted actions, such as adjusting ventilation, modifying dietary formulations, or initiating tailored treatments, thereby improving the overall efficiency and sustainability of pig farming operations (Pandey et al., 2021). Moreover, integrating PLF technologies with machine learning algorithms has the potential to further refine group monitoring. Predictive models can analyze large data sets to identify subtle patterns that may precede clinical signs of disease, enabling even earlier intervention (van Klompenburg and Kassahun, 2022). However, a significant limitation remains: the inability to address individual variability within the group. Future developments in PLF systems should aim to combine group-level monitoring with individual identification technologies, such as RFID tagging or computer vision, to bridge this gap and enhance precision management practices. According to Jacobs and van Erp-van der Kooij (2021), timely interventions driven by PLF technologies not only reduce health risks but also promote animal welfare and farm profitability. Moving forward, the development and adoption of more sophisticated monitoring systems will be crucial for addressing the complex challenges of sustainable pig production.

An example of a tool that considers an individual's status to facilitate group management is vaccination technology. Vaccination in pigs is a labor-intensive process requiring manual administration (Robbins et al., 2023). To streamline this process, automated syringes have been developed, reducing labor demands and ensuring consistent dosage delivery. Key parameters, such as the injected product volume, are centrally configured and monitored for each device. These systems provide alerts when the vaccine bottle or needle needs to be replaced, ensuring seamless operation and minimizing disruptions. These advanced devices transmit and receive data via Wi-Fi and can be controlled through a tablet or smartphone. Real-time information is provided on critical metrics, including the number of injections administered, missed injections, remaining vaccine volume in the bottle, and the vaccine temperature (Halim, 2019). Although the administration remains manual, automated syringes represent a significant step forward in modern livestock management, improving efficiency, precision, and traceability in pig vaccination practices.

MONITORING AND PREDICTIVE MAINTENANCE OF TECHNICAL SYSTEMS

Monitoring technical systems in livestock farming can be as critical as monitoring the animals themselves. A failure in the ventilation system, for instance, can rapidly have severe consequences for the animals and the farm. Delayed maintenance may lead to catastrophic outcomes such as fires, as well as seemingly minor issues such as uneven feed distribution or suboptimal climatic conditions, both of which can have significant long-term effects on animal health and productivity. Although these problems can sometimes be detected through animal monitoring, it is preferable to prevent or even predict potential system failures in advance. This is the focus of predictive maintenance, an emerging area of agricultural research aimed at preventing technical issues (Lüttenberg et al., 2018). Maintenance of automated systems can be applied to 3 primary apparatuses: climate control systems (e.g., fans and heating), feed distribution systems, and water systems.

Preventive maintenance involves scheduled actions, periodic system checks, and the replacement of components prone to damage (Satta et al., 2017). In contrast, predictive maintenance leverages sensors to detect early signs of wear or damage in system components. These sensors provide data on machine characteristics such as tension, sound, and vibration. By integrating these data with machine learning algorithms, predictive maintenance systems can calculate the likelihood of failures, enabling timely interventions before critical thresholds are exceeded (Lee et al., 2019). In livestock farming, several mechanical systems can be equipped with sensors to facilitate predictive maintenance. For climate control systems, one of the most dangerous events to prevent is a fire, often caused by anomalies in the electrical system. In this case, predictive maintenance relies on current sensors, fuse monitoring, or devices that detect abnormal electrical loads and faulty wiring before ignition occurs (Kim and Lee, 2022). In contrast, temperature sensors positioned near high-risk areas provide early detection once overheating begins, thereby minimizing severity, although not strictly predicting the event. Fans can also be equipped with integrated sensors that monitor rotation speed, energy consumption, and vibration, generating alerts before mechanical breakdown occurs (Hashemian, 2011).

Feed distribution systems can also benefit from predictive monitoring (Owusu et al., 2021). Augers and conveyors are prone to mechanical wear, blockages, or motor overload. Sensors that monitor motor current, vibration, or torque can detect irregularities in feed flow and mechanical strain before complete failure occurs, preventing both feed shortages and unnecessary downtime (Xu et al., 2020; Owusu et al., 2021; Hassan et al., 2024).

Similarly, water delivery systems can be monitored for signs of leakage, clogging, or pump malfunction (Bajany et al., 2022). Flow meters, pressure, and acoustic sensors can

detect abnormal flow rates or pressure drops that indicate early-stage problems in pipes or pumps (Rizal et al., 2022; Cugueró-Escofet and Puig, 2023; Joseph et al., 2024). Predictive analytics applied to these data streams allows early intervention, ensuring an uninterrupted water supply and reducing the risk of welfare and health issues caused by water deprivation (Joseph et al., 2024).

Predictive maintenance, therefore, offers the potential to transform the management of technical systems in pig farming. By combining sensor data with advanced analytics, these systems not only detect issues early but also enhance the efficiency and reliability of farm operations. This proactive approach ensures that technical failures are addressed before they escalate, safeguarding both animal welfare and farm productivity.

Although most large automated farms already implement backup plans, emergency fail-safes, and auxiliary power systems that are routinely tested, the consequences of malfunctions during critical periods can still be significant. Even short-term failures may disrupt farm operations, require external technical assistance, and cause stress to farmers. Moreover, delays in identifying the underlying technical issues may compromise animal welfare, for example, through overheating or inadequate ventilation (Tuytens et al., 2022). Precision livestock farming-based predictive maintenance, therefore, complements existing backup systems by enabling earlier detection and reducing the likelihood of failure.

APPLICATIONS

The adoption of PLF technologies in swine production can support more efficient and proactive herd management. Practical applications include real-time health monitoring via sensor-based systems, early disease detection via sound and image analysis, and improved resource efficiency with automated feeding and climate control. These tools enable producers to make data-driven decisions, reducing production losses and optimizing management strategies. Successful implementation of PLF requires alignment among technology, farm infrastructure, and human management. Producers should consider the economic feasibility of these tools, the availability of technical support, and the integration of PLF outputs into daily decision-making routines. Training of farm personnel is essential to ensure correct interpretation of alerts and effective responses, particularly when using video- or audio-based monitoring systems.

Precision livestock farming technologies are most effective when implemented as part of a broader management strategy rather than as stand-alone solutions. Clear protocols, regular feedback, and transparent communication with farm workers can enhance acceptance and proper use of monitoring systems. When appropriately applied, PLF can contribute to improved animal welfare, reduced production losses, and increased transparency of swine production systems, supporting both farm performance

and societal expectations for sustainable pork production.

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NOTES

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Nonstandard Abbreviations Used: AI = artificial intelligence; EFS = electronic feeding stations; EFSA = European Food Safety Authority; IMU = inertial measurement unit; PLF = precision livestock farming; PRISMA = Preferred Reporting Items for Systematic Reviews and Meta Analyses; RFID = radio-frequency identification; UHF-RFID = ultra-high-frequency RFID; WoS = Web of Science.

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