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REVIEW ARTICLE

Smart technologies to improve the management and resilience to climate change of livestock housing: a systematic and critical review

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ABSTRACT

Smart technologies such as sensors, data analytics, and automated systems could play a crucial role in enhancing the resilience of livestock housing to climate change. By providing precise and timely data, these technologies enable better resource management, early detection of stressors, and adaptive responses to environmental changes. However, a comprehensive and critical evaluation of their potential role and current applications in improving the sustainability and adaptability of livestock systems to climate change is still lacking. This research provides a first investigation of the role of smart technologies in addressing climate change challenges within the livestock sector and identifies critical areas for future research and development. A systematic and critical review of 131 papers published between 2018 and 2024, focusing on the application of smart technologies to enhance the resilience of livestock housing to climate change, was carried out. The articles were categorised based on the main livestock farming systems (dairy cows, pigs, poultry, small-ruminants, and pasture-based systems) and the type of smart technologies used, including wearable and non-wearable devices for monitoring animal health and behaviour, as well as systems for controlling environmental conditions in livestock housing. The results revealed that while smart technologies are predominantly used to monitor animal behaviour and health, their application in controlling environmental conditions is still limited. Wearable devices are extensively used in dairy cows and small ruminants, whereas non-wearable devices are more common in pigs and poultry. Future research should focus on advancing sensor technology, integrating data-driven management, and enhancing communication between sensors and farmers.

HIGHLIGHTS

- Smart technologies are primarily used to monitor animal behaviour and health
- Wearable devices are the most widely used in dairy cows, pasture-based systems, and small ruminants.
- Integrating sensor data could be crucial for rapidly identifying stressed and sick animals

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Livestock housing; climate change; precision livestock farming; smart technologies

Introduction

The livestock sector is currently facing significant challenges such as the rising demand for animal products and increasing concerns about environmental sustainability and animal welfare (Kopler et al. 2023). Climate change may exacerbate these challenges by altering ecosystems, reducing the availability of bioresources, and increasing the frequency of extreme weather events, impacting feed supply, and animal health (Choudhary et al. 2024).

The Precision Livestock Farming (PLF) approach could offer promising solutions to these challenges by utilising smart technologies such as sensors, automated systems, and data analytics. These technologies provide significant advancements in monitoring animal health and behaviour, optimising production, and

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potentially addressing climate change challenges (Papakonstantinou et al. 2024).

In the context of climate change, sensors can be used to monitor related factors such as temperature, humidity, and emissions, as well as animal feed intake, behaviour, and health parameters (Papakonstantinou et al. 2024). Additionally, smart systems could improve animal management at pasture and water usage, contributing to more sustainable practices in response to wide fluctuations of weather patterns (Herlin et al. 2021).

While advancements in PLF technologies have demonstrated potential for enhancing sustainability and adaptability in livestock systems, there remains a lack of consolidated knowledge on their specific role in mitigating the impacts of climate change. Despite scattered studies on individual technologies or species, a systematic understanding of how smart technologies collectively address key climate challenges—such as extreme weather events, resource scarcity, and gas emissions—is missing. This review aims to fill this gap by answering the following research questions: (1) What are the primary types of smart technologies currently employed in livestock farming systems? (2) How do these technologies monitor and respond to climate-related and animal-based variables? (3) What strategies have been adopted to integrate these data-driven approaches into climate-resilient livestock management practices? By analysing research from 2018 to 2024, this review contributes to the field by providing critical insights into the effectiveness, limitations, and future potential of PLF technologies for climate adaptation in various livestock farming systems (dairy cows, pigs, poultry, small ruminants, and pasture-based systems). This timely exploration is significant given the accelerating impacts of climate change on

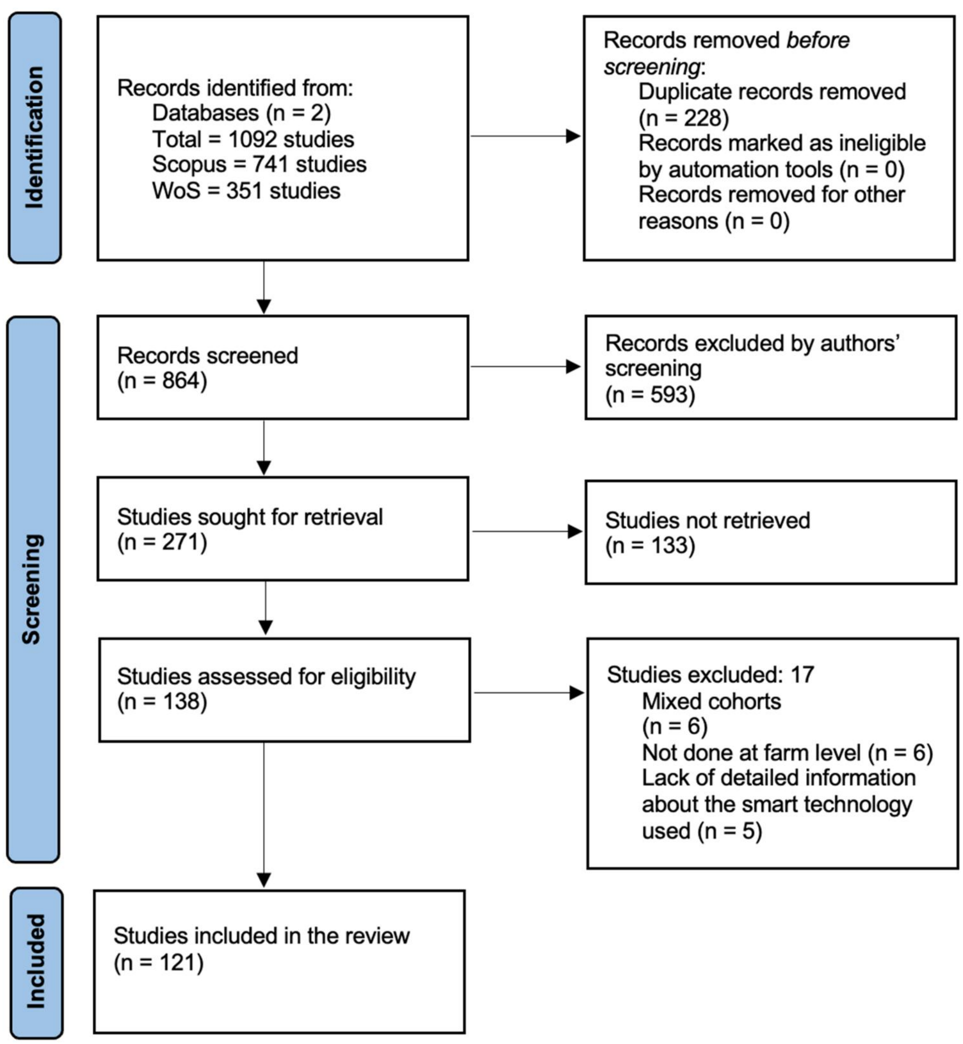

Figure 1. Flowchart of the research article selection methodology according to PRISMA (Page et al. 2021).

livestock farming and the urgent need for sustainable and scalable solutions.

Field of analysis and research methodology

The methodology applied in this research comprised three stages (Figure 1). First, the definition of the field of analysis, establishing the fundamental concepts for the search. Second, the creation of the search string, which was then executed on Scopus (Elsevier; https://www.scopus.com) and WoS (Web of Science; https://www.webofscience.com) databases to identify relevant articles. Third, the extraction of the information from the selected articles, followed by their analysis and discussion.

The present study analysed research conducted from 2018 to 2024 on smart technologies applicable to the livestock sector, particularly focusing on their applications to evaluate and manage the resilience of livestock housing to climate change. Based on the research objectives, keywords related to three key concepts were identified and used to define the search string on the Scopus and WoS databases (Figure 1): (*i*) types of smart technologies, (*ii*) environmental variables, and (*iii*) animal behaviour and physiological variables (Table 1).

The resulting string was applied through the title, abstracts, and keywords indexed by the Scopus and WoS databases as they collect most scientific publications. This approach allowed the search to be refined using a series of filters, specifically articles from 2018 to 2024 in English, and including only articles, reviews, and conference papers. This choice enabled the inclusion of numerous articles to establish a more complete framework of the topic. However, a downside of this approach was that upon examining the articles individually, many (84% of the articles) were found to be unrelated to the topic and, therefore, not usable. This was because, in the abstract, the words from the research string were randomly present, but the actual topic differed from the targeted research areas.

This literature review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, employing an evidence-based checklist connected to a three-phase flow diagram: identification, screening, and inclusion (Page et al. 2021) (Figure 1). The search produced a total of 1092 documents published between 2018 and 2024. The articles were analysed individually and filtered to select only those relevant to the research (271 articles) (Figure 1). Among the studies sought for retrieval, the following exclusion criteria were applied: 1) articles that mentioned smart technologies (e.g. sensors) without them being the subject of study; 2) articles that mentioned livestock buildings or species incidentally, without them being the subject of the study; 3) articles not done at farm level or that lack of detailed information about the smart technology used were excluded. Then, after selection, a total of 121 articles were included in the review.

To better understand how different technologies can aid to improve the resilience of livestock to climate change, studies were mainly screened for reporting technologies assessing animal-based and environmental-based categories, as animal health and behaviour as well as environmental conditions are two key points in the monitoring of climate change resilience.

A first section of the review comprised the first categorisation of articles based on the type of smart technologies used to monitor animal health and behaviour. Per each livestock category, technologies were mainly divided into wearable and non-wearable devices. The second categorisation of articles included the type of smart technologies used to monitor and control environmental conditions in livestock housing, including temperature, humidity, light, gas emissions and wind speed. Finally, once the available information about smart technology was reviewed, the third

Table 1. Number of research articles (between brackets) and type of sensors and smart technologies identified per each livestock farming system.

Research concepts	Keywords	
Smart technologies	Accelerometer, 'Embedded system*' 'Environmental control system', 'Environmental Engineering', gyroscope, 'Implantable biosensor', iclf, 'Integrated systems', 'Internet of things', 'Precision livestock farming', 'Real-time data acquisition', 'Real-time monitoring', Remote monitoring system', sensor*, 'Smart monitoring systems', 'Wearable sensor*', 'Wireless networks'	Bovine, cow*, pig*, swine, poultry, chicken, hens, broiler*, turkey*, rabbit*, buffalo*, sheep, ewe*, goat*
Environmental conditions	'Climate conditions', 'Climatic factors', environment, environmental, 'Heat stress', humidity, 'Livestock building', 'barn', 'Livestock housing', 'Relative humidity', THI, temperature, radiation	
Animal behaviour and physiology	'Animal behaviour', 'Behaviour recognition', 'Cow behaviour', 'Feeding behaviour', 'skin temperature', 'body temperature', 'respiration rate', 'Lying duration', 'Lying time', 'milk yield', 'milk production', 'meat yield', 'meat production'	

section analysed current approaches and methodologies, especially those based on data collected by smart technologies, to manage livestock housing to improve resilience to climate change. Each section was then divided according to the main livestock categories (dairy cows, pigs, poultry, small ruminants, and pasture-based systems).

Sensors and technologies to monitor animal health and behaviour

Dairy cows

Smart technologies have been mainly adopted to monitor dairy cows' health and behaviour (Figure 2). Accelerometer-based systems are the most widely used and validated technology for continuous, real-time, and autonomous monitoring (Table 2). Pedometers, collars, and ear tags can monitor the movement of legs, head, or ears to provide information on the time spent feeding, ruminating, and activity (Leliveld et al. 2023; Ranzato et al. 2023; Porto et al. 2024). The combination of accelerometers and other herd data may help at detecting altered physiological states such as hyperthermia, mastitis, lameness, (Borghart et al. 2021; Islam et al. 2021; Khan et al. 2024). These devices can also transmit ultra-wideband (UWB) radio pulses that, through radio receivers, determine specific positions of the animal in the barn with an overall accuracy of 96.79% (Dang et al. 2024). Halters equipped with accelerometers and a pressure sensor allow the observation of motor activity as well as ruminating, eating, and drinking behaviour (Antanaitis et al. 2020).

Among non-wearable devices, cameras are the most used (Table 2). They allow for continuous monitoring of animals without any physical contact and behaviour analysis through image processing with deep learning (Fuentes et al. 2023). 3D cameras with specific algorithms can monitor growth, nutritional status, and udder health with a mean absolute error of 0.7 cm for stature, 0.61 cm in rump angle, 2.5 cm in rump width, and 0.79 cm in front teat length (Lee et al. 2024). Body temperature change can be measured using infrared thermography as a method for detecting fever or inflammation. The measure of hoof temperature by infra-red technology in combination with an accelerometer to evaluate animal activity allowed the development of a lame cow detecting tool reaching 75% with clinical diagnosis (Chiu and Hsu 2022).

Tail sensor capturing skin temperature and behavioural variables (activity intensity, lying time, posture change, and tail raising) allowed to develop of a model predicting calving time within the next 24 h with a sensitivity of 97% and a precision of 80% (Higaki et al. 2022). The ruminal bolus is a wireless device administered orally and designed to remain in the animal's reticulum, allowing for monitoring of animal rumination behaviours and rumen pH and temperature (Antanaitis et al. 2022). An injectable passive RFID biosensor was developed to wireless transmitting the cow's subcutaneous temperature in real-time. On average, the difference between a body and

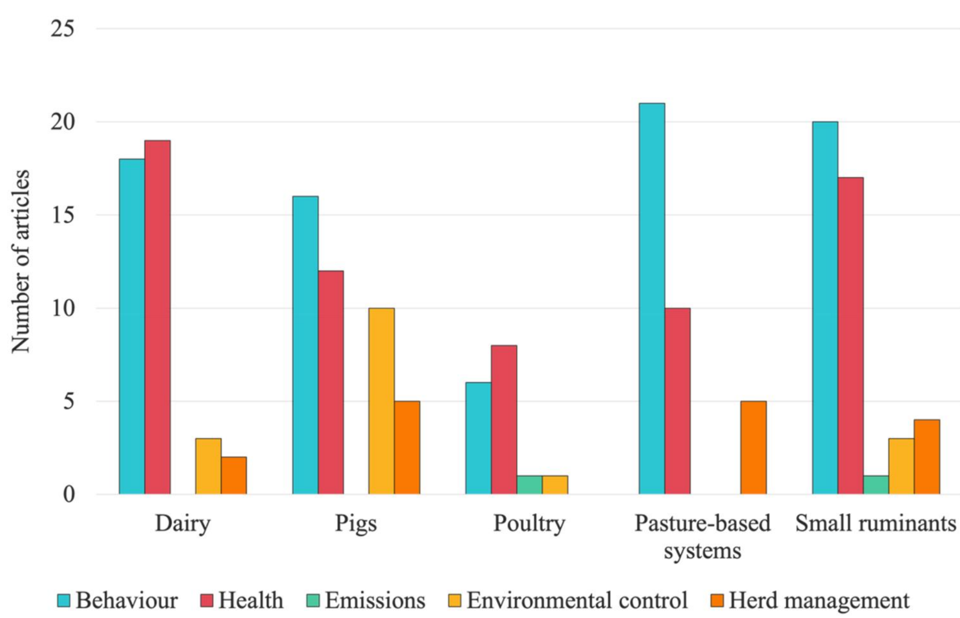

Figure 2. Number of articles per type of variable monitored or controlled through smart technologies in different livestock farming systems.

Table 2. Number of research articles (between brackets) and type of sensors and smart technologies identified per each livestock farming system.

Livestock category	Type of sensors: Wearable sensors	Non-wearable sensors
Dairy cows	Accelerometer (13) Ruminal bolus (2) Intravaginal sensor (1) Multi-sensor device (1)	Microphone (1) Video camera (3)
Pigs	Accelerometer (7) Body temperature (4)	Microphone (1) Ultra-wideband (1) Infra-red camera (11) Video camera (8)
Poultry	Accelerometer (1)	RFID (1) Infra-red camera (3) Video camera (5)
Pasture-based systems	GPS (12) Accelerometer (10) Pressure sensor (2) Urine sensor (2) Multi-sensor device (3)	
Small ruminants	GPS (6) Accelerometers (7) Multi-sensor device (3) Body temperature (6) Embedded IoT devices (5) Bit count (1)	Infra-red camera (3) Video camera (1)

GPS: Global Positioning System; RFID: Radio Frequency Identification.

subcutaneous temperature was $0.68 \pm 0.35\,°C$. Based on a multivariate polynomial regression model, which includes cow's health and production information, the body temperature of a cow was accurately predicted based on ear subcutaneous temperature with an average error of about $0.11\,°C$. These devices could be used to implement automated control-loop systems that enhance management strategies meant to identify heat stress and promptly mitigate its effects (Chung et al. 2023).

Pigs

In the pig sector, several studies explored the potential to measure animal temperature for monitoring health status and for oestrus detection. The most effective technologies in measuring pig temperature are infra-red sensors or infra-red thermography (Table 2) (Redaelli et al. 2024). In piglets, infra-red thermography has been employed to measure ear temperature and regression models and a machine learning model has been tested to predict rectal temperature, showing good performance (standard error of $1.5 - 1.7\,°C$) (Xiong et al. 2023). In lactating sows, infra-red thermography of the mammary gland provided similar information compared to rectal temperature, helping to identify diseased animals (Rosengart et al. 2022). Nevertheless, an alternative to infra-red technologies is using ear tag thermometers to measure skin temperature, showing good performance (r^2=0.69 between the mean and the standard deviation of the time series of temperatures of each animal) in discriminating animals with different thermal patterns (Garrido-Izard et al. 2019).

Several models have been proposed to predict body temperature from environmental data. For instance, deep neural networks have been shown to provide the best prediction for rectal temperature with an error of 0.36% (Gorczyca et al. 2018), while regression models successfully predicted pig body temperature based on thermal humidity index (THI) (Basak et al. 2020).

Pig behaviour has been widely used as an indicator of animal welfare. However, the approaches used to determine animal position and movement were different across the studies. For instance, a common approach is to use image analysis of surveillance videos, achieving 90.5% accuracy in recognising sow nursing behaviours (before piglet sucking, piglet sucking, and end piglet sucking) with a deep neural network model (Li et al. 2023). Similarly, aggressive behaviour has been extracted from surveillance video by adaptively fusing spatial and motion information with a method based on a deep neural network with an Average Precision value of 68.0% and an Average Recall value of 77.8% (Yan et al. 2024).

When sow behaviour was monitored using a 3D camera installed in farrowing rooms, posture classification accuracies by the processing program were more than 99% compared to human labels (Leonard et al., 2019). Similar results have been obtained using a 3D radar, obtaining a classification of standing and lying postures with a mean balanced accuracy greater than 90% (Henry et al. 2023). Besides video surveillance, the movement of pigs in the pen can be detected with the use of ultra-wideband (UWB) technologies that can track pig position with an error lower than 0.5 m (Zhuang et al. 2020) and accelerometers (Knoll et al. 2024). Finally, passive infra-red detectors showed a strong correlation ($r > 0.76$, $p < 0.001$) with visual observation in monitoring pig group activity (Wurm et al. 2023).

Poultry

In small livestock species such as poultry and rabbits, technologies to monitor animal behaviour and health include a wide range of non-contact or contact devices. The former included image analysis applications using video cameras (Pereira et al. 2020a; Del Valle et al. 2021), infrared cameras (Zaninelli et al. 2018), and thermal cameras (Bloch et al. 2020). The latter is based on sensors fitted on animal bodies, including wearable or subcutaneous accelerometers (Reynolds et al. 2019; Wu et al. 2022; Chen et al. 2023) and radio frequency identification systems (RFID) (Neethirajan 2022) (Table 2).

As in pigs, the automated identification of poultry behaviours plays a pivotal role in assessing their health and enhancing their welfare and establishes a technical foundation for intelligent diagnosis and early detection of poultry diseases (Wu et al. 2022; Da Silva et al. 2023). Within poultry behaviour recognition, the main aspects analysed include feeding and drinking behaviours, movement tracking, animal distribution in the barn, and laying behaviour, which are generally detected with an accuracy ranging from 60 to 95% (Wu et al. 2022).

Among available technologies, one of the most used applications is computer vision, offering non-contact detection capabilities and providing several advantages such as abundant information, high efficiency, objectivity, and broad applicability in perceiving poultry targets (Wu et al. 2022). For instance, computer vision has been used to identify nest usage and multiple nest occupations with high sensitivity (80%) and specificity (90%) (Zaninelli et al. 2018) and to assess the level of chicken clustering to estimate animal thermal comfort (Pereira et al. 2020a; Del Valle et al. 2021). Video cameras coupled with deep learning tools have been tested amidst different backgrounds to count and track chicken movements, showing good suitability for on-farm use (Neethirajan 2022). Thermal cameras have also been tested to automatically measure individual broiler chicken temperature (Bloch et al. 2020), employing low-cost infrared cameras calibrated in real-time, which have shown high accuracy (±0.3 °C) and applicability in commercial barns (Bloch et al. 2020). On the other hand, image analysis could present some constraints, such as high data transfer and memory requirements, the negative impact of dirty environments on image quality, as well as the high number of cameras required to perform a comprehensive evaluation of animal activity in the barn, especially in multi-tier aviary systems.

As for contact devices, low-frequency RFID systems have been used to detect laying hen activity, record entries and exits from the nest box, and allow for individual monitoring of hen behaviour (Chien and Chen 2018). On the other hand, subcutaneous sensors recording body temperature changes and assessing thermal comfort have been recently tested in rabbits (Chen et al. 2023) and chickens (Reynolds et al. 2019). However, the utilisation of subcutaneous sensors may raise welfare and management concerns, including application-related stress or the requirement for highly specialised personnel to install the sensors properly.

Pasture-based livestock systems

Different sensors and devices have been used to collect data and monitor both the behaviours and health status of grazing cattle, with GPS and accelerometers being the most widely adopted (Table 2). The exclusive use of positioning data derived from GPS collars allows the monitoring of cow behaviours in terms of walking distance and lying time (Hamidi et al. 2023; Raniolo et al. 2023). For instance, Gwatirisa et al. (2022) observed that cattle raised in 80–hectare paddock overused areas near water points rather than walking long distances to abundant forage, validating GPS data through direct observation. Bio-loggers and GPS collars can provide insights into cattle movements, grazing patterns, disease control strategies and energy expenditure (Rivero et al. 2021). Factors like stocking rate, water location, and weather significantly influence animal migration patterns (Motta et al. 2018) and distribution in the pasture (Cheleuitte-Nieves et al. 2020, Neave et al. 2021). By combining GPS tracker technology with a Long-range wide area network (LoRa-WAN), it is possible to monitor the location and movements of beef cattle over extensive pastures ($5-10\ km^2$) for three months (McIntosh et al. 2023). To effectively monitor changes in animal behaviour, an appropriate data collection rate is crucial (Mancuso et al. 2023). However, a high sampling rate determines higher sensor battery consumption, reducing the overall observation time (Riaboff et al. 2020).

Collars or ear tags with accelerometer sensors have been shown to effectively monitor grazing, rumination time (Riaboff et al. 2020; Pereira et al. 2020a; Iqbal et al. 2021), and oestrus onset (Minegishi et al. 2019), with some limitations that require further algorithm refinement. In addition, triaxial accelerometers have been used to monitor reduced lying time in dairy cows due to colder temperatures and increased rainfall (Hendriks et al. 2019) or to study the genetic factors influencing basic behaviour in local dual-purpose European breeds (Yin et al. 2019). Combining motion sensors (pedometers, accelerometers) with noseband pressure sensors allows for to study of feeding behaviour (grazing, rumination, and walking) of grazing in mountain cows (Romanzin et al. 2018), as well as the ingestion patterns of cows in extensive rangelands, measuring grazing time accurately ($r = 0.95$) and bit rates with an accuracy between $0.53 < r < 0.79$ (Raynor et al. 2021). In grazing cattle, customised multi-sensors (pressure, reflective index) can be used to monitor and assess urination patterns (urination events, flow rate, frequency, volume, N concentration) (Ahmed et al. 2018; Shorten et al. 2022).

Digital twins hold promise for animal health management (Neethirajan and Kemp 2021). These virtual models integrate data from various sensors to optimise feed intake, detect disease early, and improve overall well-being. Similarly, virtual fencing for cattle is compared to electric tape fencing, showing promise for confining animals with minimal welfare impacts (Campbell et al. 2019).

Machine learning techniques can be used to predict disease risk and laying behaviour. Success has been demonstrated in risk mapping for *Fasciola hepatica* in grazing dairy cows (Cockburn 2020). Moreover, it is possible to monitor the frequency of behaviours of beef cattle at pasture (walking, grazing, ruminating, idling, water consumption frequency, feeding) using a classification algorithm for acceleration, angular velocity, and magnetic data (Schmeling et al. 2021; Watanabe et al. 2021).

Small ruminants

Advancements in smart technologies are transforming small ruminant productions by enabling the automated collection of valuable health and behavioural data.

The use of accelerometers demonstrated the potential for wearable sensors to differentiate between grazing, standing, and walking in sheep, to help in detecting lameness (Lewis et al. 2023), or to investigate the effects of social isolation of sheep (Salvin et al. 2020). Additionally, researchers have successfully used accelerometers and machine learning to classify sheep behaviour based on animal posture and activity levels (Price et al. 2022). Other studies used an attached multi-sensor tag (accelerometer, magnetometer, temperature sensor and GPS), combined with geographic information systems to assess feeding patterns, energy expenditure, and environmental factors affecting Merino sheep production (Di Virgilio et al. 2018) or examine the effects of climatic conditions on the grazing behaviour of Mongolian sheep (Horie et al. 2023). Motion sensors embedded in collars can achieve classification accuracy rates ranging from 67 – 78% (Dos Reis and White 2022) to 78 – 92% (Vázquez-Diosdado et al. 2019) for eating, ruminating, standing, and lying behaviours, through machine learning algorithms. A similar approach was used to estimate the urination volume considering the ewe squatting time from accelerometer data, resulting on an average of 2.15 ± 0.04 L per day (Marsden et al. 2021).

Different tracking systems have also been studied to determine animals' position (Walker et al. 2024; Woods and Adcock 2024). The combination of UWB technology, infrared cameras, and 3D computer vision, showed good results in monitoring small ruminants' location and behaviour with high accuracy (Ren et al. 2020). Similarly, GPS collars were used (Evans et al. 2022; Parnell et al. 2023; Tosa et al. 2023), combined with machine learning (Liu et al. 2023) or with accelerometers and weather stations (Fogarty et al. 2021), to detect lambing events, with an accuracy of up to 91%.

Heat stress management in small ruminants is a critical area where the importance of real-time body temperature data collection has been evidenced (Lewis Baida et al. 2021; Pent et al. 2021). The temperature of ewes and lambs can be measured with various methods including surgical implantation, in the abdomen or vagina, and non-invasive techniques like rumen bolus (Fuchs et al. 2019; Lewis Baida et al. 2022). Although the surgical implantation of sensors is not applicable in an agricultural setting, these sensors accurately recorded normal sheep body temperature (38.3 – 39.9 °C).

Remote-controlled systems have been developed to assess pain responses in sheep (Taylor 2020) and wearable systems have been proposed to monitor physiological parameters (e.g. heart rate and skin temperature) for behavioural and stress evaluations (Costa et al. 2018; Zhang et al. 2020), also during transport (Cui et al. 2019). While challenges regarding energy autonomy and accurate core temperature measurement persist (Costa et al. 2018; Kearton et al. 2020), these technologies hold great potential for enhancing animal health monitoring. Further research is needed to validate sensor data accuracy through ground-truth data collected *via* visual observation (Keshavarzi et al. 2021; Liu et al. 2023) and interpret sensor data (Dos Reis and White 2022).

Smart technologies to monitor and control environmental conditions

Dairy cows

Temperature and relative humidity sensors are those mainly used for monitoring environmental conditions of barns (Figure 3) and recorded data are used to implement the calculation of bioclimatic indices, such as the temperature-humidity index (THI) adopted to assess heat stress conditions in dairy cows (Leliveld et al. 2023). The orientation, width, height, and slope of the roof are specific construction characteristics that may contribute to modulating the microclimate conditions inside barns for dairy cows (Ji et al. 2020).

In recent years, interesting solutions for environmental control have been developed by integrating artificial ventilation systems in the barn, such as tunnel ventilation, which requires the use of fans and inlets to supply a continuous flow of air along the entire length of the barn (Chung et al. 2020). To enhance the performance of these systems, an evaporative panel should be put on the air intake wall, through which the incoming air will flow and cool down.

Misting devices offer the advantage of directly lowering the ambient temperature in the barn in cooling systems combining fans and water as compared to showers (Lovarelli et al. 2020). However, this strategy loses efficiency in excessively humid regions, as the minute droplets of water released tend to increase the humidity inside the barn.

Pigs

In pig farms, many studies evidenced the benefits of spatial and temporal monitoring of environmental parameters (temperature, humidity, ammonia, and carbon dioxide concentrations) (Zeng et al. 2021) (Figure 3). An advanced environmental control requires a network of sensors to be placed in the barn to map the thermal parameters (Ramirez et al. 2018a). Furthermore, more knowledge on animal response to environmental conditions has to be obtained.

In growing pigs, mechanistic models have been proposed to define thermal losses and determine body temperature through physiological and behavioural thermoregulation responses (Ramirez et al. 2018b). Another approach is to measure the body temperature using thermal infrared thermometers and use this information to control the heating or ventilation systems. This requires the presence of animals in a well-defined space, like creeps for piglets (Sartor et al. 2021). Besides the improvement of

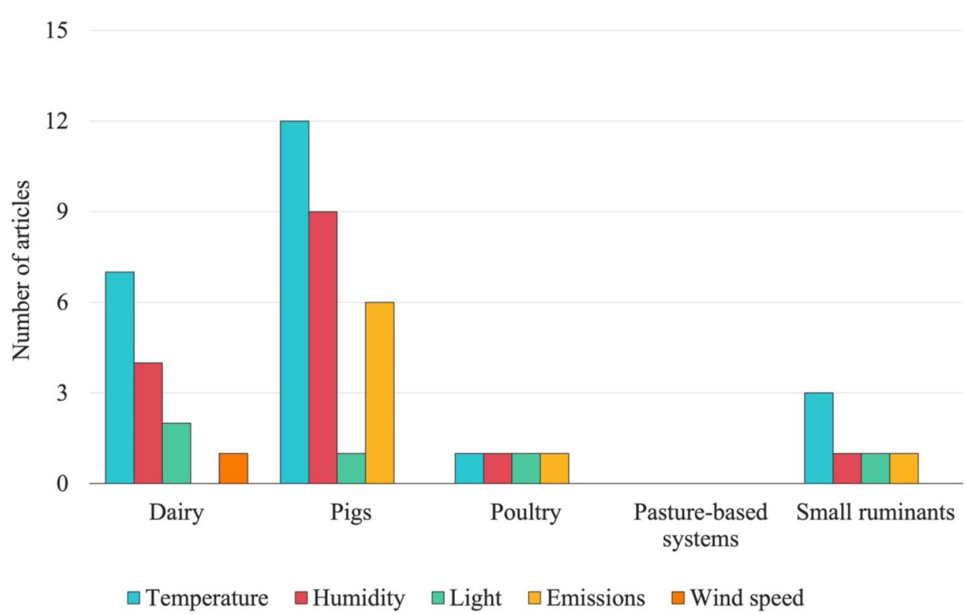

Figure 3. Number of articles per environmental variables monitored through sensors and smart technologies in different livestock farming systems.

performances, this approach can lead to energy savings. Fuzzy systems can be used to predict growth performance and physiological responses (respiratory rate, rectal temperature, and skin temperature) of piglets raised in farrowing house using as input dry bulb temperature and relative humidity with good accuracy (coefficient of determination >0.98) for physiological responses (Alves Damasceno et al. 2019).

Poultry

Available technologies to monitor environmental conditions in poultry houses can be categorised into climate and air quality sensors (Qi et al. 2023). Climate sensors like anemometers and thermometers allow for managing microclimate barn conditions (temperature, humidity, wind). In contrast, gas sensors like electrochemical or spectroscopy-based ones can monitor the concentration of harmful gases such as CO_2, and NH_3, as well as microorganisms and particulate matter (Qi et al. 2023). Nowadays, studies aim to enhance equipment portability and stability due to field constraints, addressing challenges like dust, acidic manure environments, and sensor degradation. Wireless sensor networks, proposed for efficiency and accuracy, offer promise in poultry farm monitoring (Qi et al. 2023) by potentially reducing the number of devices used and ensuring high uniformity in recording microclimate conditions at the barn level.

Small ruminants

The integration of natural elements with technology is effective in regulating microclimates for livestock. By using tree shades in pastures, a significant reduction in lamb body temperatures can be achieved during peak heat periods, as measured by intravaginal temperature sensors (Pent et al. 2021). Moreover, the research conducted by Sutherland et al. (2019) revealed the profound impact of microclimate manipulation on animal behaviour and growth. Their study explored the influence of flooring surfaces and supplemental heat sources on dairy goat kid preferences and development, revealing that providing wood shavings with heat lamps positively affects lying, running, and weight gain activities in the kids (Sutherland et al. 2019). Non-invasive temperature monitoring systems and remote pain assessment tools could offer valuable insights into animal well-being and enable more effective management practices. For instance, a monitoring system based on the integration of a central processing unit (CPU) with various sensors detecting ambient light, gases like ammonia and carbon dioxide, as well as temperature and humidity levels, was able to adjust barn ventilation and other parameters based on sensor readings, improving overall barn conditions (Rao et al. 2020).

Approaches to herd management for climate change resilience

Dairy cows

By combining environmental data with physiological parameters that can be detected, such as skin, rumen, milk, rectal or vaginal temperature, heart rate, respiration rate, sweating rate, and lying patterns, it is possible to anticipate heat stress and respond with customised interventions (Tangorra et al. 2024).

Automated rumination time monitoring was used as a potential managerial tool to predict heat stress in dairy farming, and the value of 63 units of THI was identified as the critical threshold above which high-producing cows started to reduce rumination as a consequence of heat stress, indicating the need to implement heat stress abatement strategies above this critical value of THI (Sammad et al. 2022). Compared to visual observations by barn management staff, automated camera vision-based methods for monitoring respiratory rate, although still relatively expensive, show high accuracy and can support automated cooling systems like fans in resting areas (Shu et al. 2024).

Silent heat events are difficult to detect and become frequent under heat stress. To avoid errors due to discontinuous visual monitoring by dedicated personnel, using pedometers allows for timely and successful identification and insemination of cows, thus reducing veterinary costs for re-fertilizations and milk yield losses caused by extended calving intervals (Lovarelli et al. 2023).

Genetic selection provides an effective long-term solution to counteract the negative effects related to climate change (Pryce et al. 2022). Wearable devices that record a large number of body temperature measurements allow for the creation of databases useful for the evaluation and genetic selection of more thermotolerant individuals. By focusing on breeding for heat resilience, farmers can build more robust herds that are more prepared to withstand increasing environmental challenges.

Pigs

The approach generally adopted in pig production to address the challenges of climate change is to increase the control of the production system to improve animal welfare. Different technologies can be used to monitor pig health and performances (e.g. video and sound analysis, temperature detection, weight recording) (Mahfuz et al. 2022). Automated early warning systems, based on monitoring of specific physiological and behavioural parameters, could represent a valid alternative to direct observation of animals in the barn (Racewicz et al. 2021). These systems include on-farm integrated data collection and monitoring of environmental and animal conditions, either directly with wearable sensors or with remote measurement systems or indirectly through predictive models based on regressions or artificial intelligence. Machine learning techniques were adopted to predict the welfare status of pig herds. For example, data from video analysis coupled with machine learning were used to classify the welfare status of the gestating sows in pens according to their feeding behaviour (Durand et al. 2023). Artificial intelligence applications coupled with sensors measuring body temperature, respiration rate, heart rate, and animal movement (accelerometers) have been shown to effectively evidence stress conditions of piglets reared under different environmental conditions (Neethirajan 2023). These technologies could be integrated into decision support systems to comprehensively monitor the living conditions of animals, thus contributing to climate change resilient farm management (Durand et al. 2023).

Poultry

Thermal stress has a significant impact on poultry production and behaviour. To assess and monitor thermal comfort in broiler chicken and laying hen flocks, cluster indexes (Pereira et al. 2020b) and unrest indexes (Del Valle et al. 2021) have been recently proposed. Derived from digital image analysis, these indexes measure bird behaviour through video camera capture. Findings indicate reduced clustering and increased unrest behaviours in high-temperature conditions, with breed-specific variations. For instance, Hybro birds showed lower agglomeration (cluster index about 16% lower) than Ross birds with temperatures above 29 °C. Overall, using computer vision techniques as a surveillance system to monitor the thermal comfort of poultry flocks showed utility and efficiency in early stress detection with a low computational effort (Del Valle et al. 2021). This approach has been widely adopted, especially in terms of prototypical scale, as it enables the understanding of significant information about the thermal environment and inhospitable areas through the behaviour and distribution of the poultry within the barn.

Pasture-based livestock systems

Climate change poses multifaceted challenges for pasture-based livestock farming, related to disease prevalence, parasite transmission, and heat stress. Leveraging biotic and abiotic parameters, as demonstrated in the study on Rhipicephalus ticks in dairy cattle under transhumance (Zannou et al. 2021), enables preventive measures for parasites management. Machine learning (ML) algorithms using sensor data and weather information can successfully predict milk yields and detect diseases outbreaks like in dairy cows (Cockburn 2020). These insights empower farmers to optimise resource allocation and address health issues. The estimation of thermal comfort indices through remote recording stations evidenced how the integration of trees in the pastures had a positive effect in mitigating heat stress of the animals (Magalhães et al. 2020). Recent research by Schütz et al. (2023) suggested adjusting milking schedules and feeding times to alleviate heat stress in dairy cows, highlighting tailored practices for climate resilience in livestock farming.

Small ruminants

In small ruminant management, the adoption of automated technologies for monitoring heat stress such as the use of indwelling probes, intra-ruminal bolus, thermal imaging, and implantable devices can provide real-time data on body temperature, a key indicator of heat stress levels (Lewis Baida et al. 2021). This data is vital for early detection of heat-stressed sheep, enabling farmers to take timely actions to mitigate its effects. Additionally, GPS collars have shown good potential to identify heat-stressed individuals Lewis Baida et al. (2021). Advancements of precision livestock farming (e.g. accelerometers, GPS collars, real-time monitoring devices, etc.) and parasite resistance breeding offers promising solutions for sheep and goat herders' adaptation to a changing climate (Silva et al. 2022). The use of Internet of Things (IoT) enables real-time data collection on sheep behaviour, empowering farmers to remotely monitor their herd and address environmental stressors promptly (Nóbrega et al. 2019). Managing sheep energy expenditure is another critical adaptation strategy. For instance, terrain characteristics have been shown to impact on walking distance and energy requirements during animal transhumance (Zanon et al. 2022). Farmers can optimise energy balance and ensure sheep health during alpine grazing, monitoring walking distances and adjusting feeding strategies accordingly.

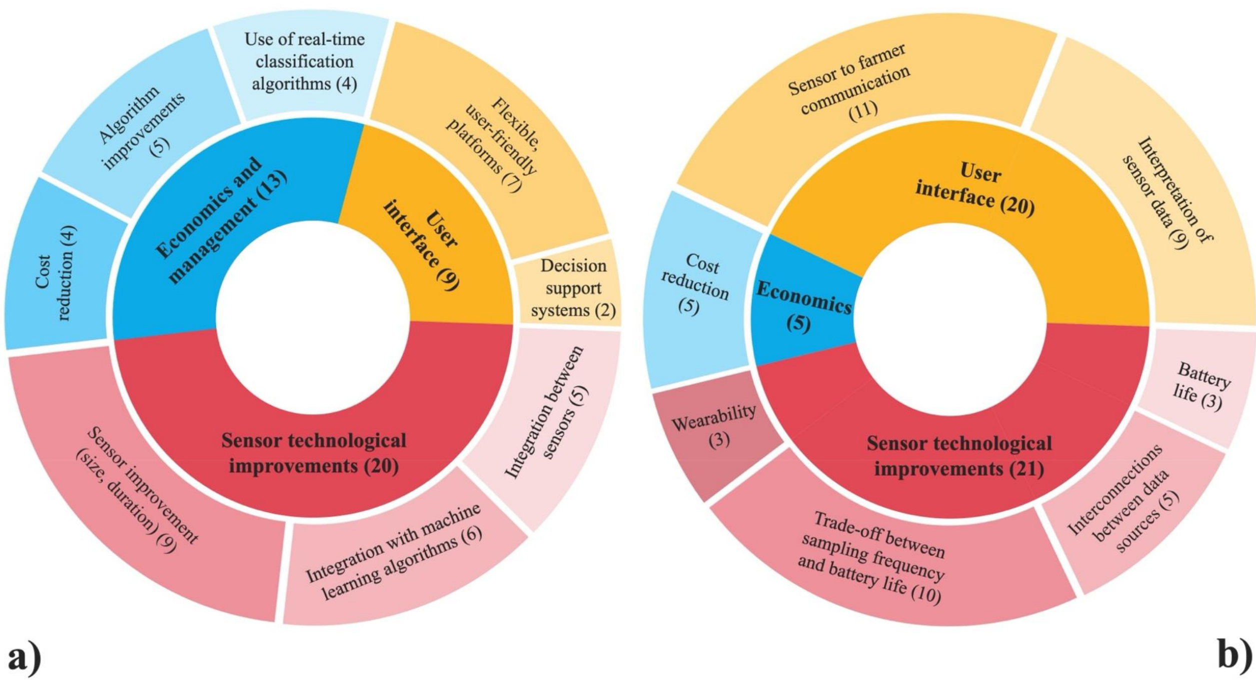

Figure 4. Number of articles identifying future areas of study (a) and possible obstacles and elements of resistance (b) for the applications of smart technologies in livestock systems to improve the resilience to climate change.

Research trends and knowledge gaps

The development of new sensors is focused on optimising technologies with smaller device dimensions, improved data transfer capabilities, and lower energy consumption (Bloch and Pastell 2020; Chung et al. 2020) (Figure 4). Extensive research in artificial intelligence and advancements in data processing methods, such as deep neural networks, are continuously enhancing the accuracy and robustness of algorithms that interpret animal behaviour. In the future, behavioural data should be integrated and contextualised with other sensory data to provide a comprehensive overview of animal health and assess adverse effects (Kurras and Jakob 2024).

The adoption of new technologies is challenged by several factors, including the level of management required for implementation, structural constraints for installation, farmers' lack of knowledge, and varying levels of interest in specific technologies. Additionally, high initial costs, uncertainties regarding return on investment, maintenance costs, and the need for qualified personnel may further limit their diffusion (Kaur et al. 2023) (Figure 4).

For large animals such as cows, pigs, sheep and goats, a significant consideration is the time required for animals to acclimate to wearable devices before useful data can be collected (Buijs et al. 2023). Invasive devices can cause discomfort, negatively impacting their welfare and altering the behaviours intended to be monitored, which has led to an increased focus on contactless technologies (Wang et al. 2021). In this context, image analysis appears to be the most promising technique for monitoring pigs and poultry, while wearable sensors, although available, are less attractive for practical applications.

The frequency of data recording by sensors and tools is crucial. While sensor monitoring could generate substantial amounts of raw data, the processes of storing, transmitting, analysing, and modelling this data demand significant energy and computing power—resources often lacking at the farm level (Figure 4).

Another challenge in implementing smart technologies in livestock housing is the low integration of multiple data sources, especially for commercial sensors (Figure 4). The interlinking of various monitoring systems will be crucial for data-driven dairy farm management. A further key issue is related to the battery life of the monitoring devices that currently result to be too low for an adequate data sampling frequency (Figure 4). Additionally, the development of user-friendly platforms for presenting information is essential, as effective communication between sensors and farmers—especially for free-grazing animals—remains a challenge.

Conclusion

This paper analysed scientific articles on the use of smart technologies in the livestock sector, focusing on their role in enhancing the resilience of livestock housing to climate change. A total of 1092 articles published between 2018 and 2024 were reviewed, with 121 selected for in-depth analysis. This review has limitations, including the use of only two databases, which may have excluded relevant publications and the focus on English-language articles, potentially omitting significant works in other language. In addition, the review did not consider the specific use of smart technologies in different farming contexts such as organic, intensive, or mountain farms.

Overall, our findings can be summarised in four key points:

i. Smart technologies are primarily used to monitor animal behaviour and health, with limited application in monitoring and controlling environmental conditions.
ii. Wearable devices are the most widely used in dairy cows, pasture-based systems, and small ruminants. They monitor animal activity via GPS and accelerometers, and track reproduction phases and heat stress using invasive thermometers, buttons, and boluses. Non-wearable devices, such as video cameras for behaviour monitoring and infra-red cameras for heat stress detection, are mainly used in pigs and poultry.
iii. To enhance livestock resilience to climate change, integrating sensor data on respiratory activity, body temperature, heart rate, and movement could be crucial for rapidly identifying stressed and sick animals, especially in dairy cows, small ruminants, and pigs. In poultry, combining video cameras with artificial intelligence could help compute cluster and unrest indexes.
iv. Future research should focus on advancing sensor technology by reducing size, improving wearability, and extending battery life. Additionally, integrating and managing large data sets from multiple sensors, implementation of artificial intelligence and enhancing communication between sensors and farmers will be critical areas for future development.

Authors'contribution

All authors have contributed equally to the work.

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Data available on request from the corresponding author

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