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Review

May the Extensive Farming System of Small Ruminants Be Smart?

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Abstract: Precision Livestock Farming (PLF) applies a complex of sensor technology, algorithms, and multiple tools for individual, real-time livestock monitoring. In intensive livestock systems, PLF is now quite widespread, allowing for the optimisation of management, thanks to the early recognition of diseases and the possibility of monitoring animals' feeding and reproductive behaviour, with an overall improvement of their welfare. Similarly, PLF systems represent an opportunity to improve the profitability and sustainability of extensive farming systems, including those of small ruminants, rationalising the use of pastures by avoiding overgrazing and controlling animals. Despite the livestock distribution in several parts of the world, the low profit and the relatively high cost of the devices cause delays in implementing PLF systems in small ruminants compared to those in dairy cows. Applying these tools to animals in extensive systems requires customisation compared to their use in intensive systems. In many cases, the unit prices of sensors for small ruminants are higher than those developed for large animals due to miniaturisation and higher production costs associated with lower production numbers. Sheep and goat farms are often in mountainous and remote areas with poor technological infrastructure and ineffective electricity, telephone, and internet services. Moreover, small ruminant farming is usually associated with advanced age in farmers, contributing to poor local initiatives and delays in PLF implementation. A targeted literature analysis was carried out to identify technologies already applied or at an advanced stage of development for the management of grazing animals, particularly sheep and goats, and their effects on nutrition, production, and animal welfare. The current technological developments include wearable, non-wearable, and network technologies. The review of the technologies involved and the main fields of application can help identify the most suitable systems for managing grazing sheep and goats and contribute to selecting more sustainable and efficient solutions in line with current environmental and welfare concerns.

Keywords: sheep; goat; extensive system; Precision Livestock Farming (PLF); sensor

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1. Introduction

Livestock management practices that rely solely on farmers' observations, judgment, and experience may not meet the requirements of modern livestock farming. Therefore, precision agriculture, with the support of information technologies, has become an inevitable innovation in contemporary breeding. Due to the urgent need to integrate new technologies, artificial intelligence, and innovative animal husbandry development, the livestock industry is rapidly advancing toward a new era of fusion-integrated innovation [1]. Digitalisation has become an integral part of animal husbandry production and refers to various innovations such as automated milking systems, sensor technology, and electronic data processing. In recent years, the research on "Precision Livestock Farming" (PLF) has made significant progress in improving the economic, environmental, and social sustainability of livestock production [2,3]. PLF is a multidisciplinary concept that describes a complex of sensor technology, algorithms, and applications for gathering information to enhance both the production system as well as the welfare and health of the animal and the environment [4–6]. The interaction of sensors and information technologies facilitates farm management, allowing for fewer veterinary interventions, behavioural identification in real time, feeding and reproduction optimisation, and lots of data available for the evaluation of the productive and reproductive conditions of individual animals, their physiological states, and environmental factors [7]. Intelligent systems could be used to monitor climate change-related factors, such as temperature, humidity, and emissions [3], or to improve grazing animal management and water use, contributing to more sustainable practices in response to large fluctuations in weather patterns [8]. Highly productive animals are more susceptible to heat stress; on the contrary, local and more rustic populations are more resilient to harsh climates thanks to different morphological and genetic adaptations to their developed environments [9]. PLF provides farmers with objective and continuous data collection directly on smartphones and computers, making it possible to improve management by promptly correcting one or more production inputs, the early recognition of diseases, and the monitoring of changes in animal behaviour. The application of PLF technologies has been most developed in dairy cows, considered high-value animals, to be monitored in various aspects, such as physiological [4], reproductive, behavioural, and productive aspects [10]. PLF technologies can provide crucial information on calf growth and health status, addressing increasing concerns for the welfare of young animals. Monitoring devices and sensors in cattle farming enable real-time livestock health and location monitoring and improve animal welfare [11,12].

In recent years, various technologies have been developed to measure and predict animal body parameters to improve the maintenance of health and to maximise production efficiency—boluses, collars, radio frequency identification device (RFID) tags, noseband sensors, camera analysis models for position detection and methane emission estimation, and sound analysis systems for dairy production [12–14]—in dairy goats [15,16], cow [5], poultry [17], and pigs [18].

Integrating intelligent technologies based on artificial intelligence (AI) and machine learning (ML) has transformed the beef and dairy cattle sector. The evolution of equipment, sensor technology, and new algorithms has enabled animal management and welfare optimisation, identifying anomalies, minimising risks, and maximising productivity [12–14]. The use of new technologies helps increase transparency and traceability, thus promoting customer trust and improving food safety measures [18].

The central sheep farming regions are Australia, South America, New Zealand, Northern Europe, and Asia. These include developed countries with high concentrations of sheep raised with relatively traditional approaches compared to cattle: high feed costs, vulnerability to predation, animal health problems, and negative environmental impacts [12–14,19]. Small ruminant farming occupies a significant place in the Italian agricultural landscape, and sheep and goats represent about 10% of the total ruminant population in Italy. They are mainly present in some marginal areas, and over the last five years, there has been a reduction in the number of small farms and livestock [12–14,20]. The population has about five million sheep and nine hundred thousand goats. A notable decrease in the number of farms has been noted, particularly in small family-run farms [12–14,20]. Traditional extensive or semi-extensive farming, although still the predominant type for sheep and goats, must face challenges such as the abandonment of less profitable activities, reductions in the number of pastures, and the crisis in the wool market [12–14,21]. However, the structure of these farms has changed; large modernised farms are increasing in number, especially in the dairy sheep sector. A substantial part of the population of small ruminants, more than two-thirds, is mainly located in Sardinia [12–14,20]. With improved Precision Livestock Farming (PLF) practices, farmers are encouraged to adopt digital solutions for their sheep farms. They aspire to maximise profits by optimising costs and revenues through improved animal welfare, which is directly linked to higher yields. Bordignon et al. [12–14] have analysed that the development of new sensors is focused on optimising technologies with smaller device dimensions, improved data transfer capabilities, and lower energy consumption. Applying these tools to intensive systems has produced excellent results thanks to elements adapted to the needs of digitalisation. Odintsov Vaintrub et al. [1,16] have reported on these elements, including environmental conditions, information and communication technologies, and perimeter areas [1,16]. Moreover, climate instability, consumer tastes, sustainable development goals, and production efficiency have also constrained all farmers [12–14,21]. With reductions in water availability, climate change negatively affects the quantity and quality of pasture and the production of feed for livestock. The extensive sheep and goat sector has seen a decline in the ratio of animal care workers to the total number of animals. Consumers have shifted their dietary preferences to favour animal-based proteins, mainly beef and cheese [12–14,22]. These challenges are even more pronounced in extensive mountain systems, where high altitudes, steep slopes, and significant climatic variations make access and animal monitoring difficult. Consequently, these factors prevent the routine implementation of PLF within the production process in extensive systems [12–14,23]. However, Odintsov Vaintrub et al. [1,16,24] have reported that the application of intelligent systems enables extensive sheep farmers to strengthen sales, the integration of digitalisation and artificial intelligence (AI) has improved particularly intensive sheep farming, with greater efficiency in production yield and animal health status. Morrone et al. [12–14,19], in fact, have highlighted that the combination of sensors and artificial intelligence (AI) can detect animal welfare on farms and during transportation.

With the development of new sensor technologies and infrastructure for data transfer, the gradual application of these systems in grazing animals is now possible [3,25]. Extensive farmers prioritise grazing methods with low financial investment and relatively simple management, which provide economic resilience to market fluctuations. Therefore, adding PLF systems would inevitably increase production costs and add another layer of technological complexity to farm management, causing delays in implementing PLF systems in small ruminants compared to those in dairy cows [15]. The unit prices of sensors for small ruminants are higher than those developed for large animals due to miniaturisation and higher production costs associated with lower production numbers. Sheep and goat farms are often located in mountainous and marginal areas, with poor technological infrastructure and unreliable electricity, telephone, and internet services. They are associated with advanced age in farmers, contributing to poor local initiatives and delays in PLF implementation [16].

Nevertheless, developing and applying small ruminant grazing technologies are particularly interesting for economic and environmental sustainability. PLF system results and artificial intelligence (AI) are fundamental for farmers for animal control [19].

Indeed, interest has grown in the past five years, and several PLF applications have been developed. Efforts have focused primarily on systems designed for managing grazing animals. These have included virtual fences, drones [26,27], collar-mounted devices connected to each animal, and software to define the locations of enclosures. A collar emits a warning sound when an animal approaches a virtual fence. A mild electric shock is given if it crosses the fence, which is harmless but uncomfortable [28]. The development in precision grazing technologies ranges from image analysis for grazing measurements [29–31] to systems for the electronic identification of animals such as RFID tags [25], multiple motion detection sensors such as accelerometers [24], and GPS [15], helpful for health status and well-being assessment [32,33]. Precision technologies bring significant advantages in extensive rearing systems but require continuous improvements and updates to support farmers in management decisions [34].

According to Tuyttens et al. [35], PLF can pose threats to farms such as direct damage to animals from technical failures of hardware components, inaccurate predictions by the farmer, and negative effects on the animal's welfare state. Using sensors and technologies to rear small ruminants also presents challenges related to various factors such as farmers' reluctance to adopt new technologies, the high cost of these instruments, and the strong attachment to traditional practices. Additionally, customizing these tools for small ruminants and validating their use for sheep and goat species is a complex and time-consuming process that hinders the widespread adoption of these technologies. According to Odintsov Vaintrub et al. [24], these limiting factors for the broader adoption of innovative technologies in extensive farming may be overcome considering the emerging economic and environmental trends allowed by the more innovative part of the farmer population. This study aimed to conduct an investigation of PLF application in the extensive small ruminant sector based on a review of the literature from the past 5 to 7 years. The focus here will be on both wearable and non-wearable sensors that provide insights into animal behaviour in extensive farming systems, specifically regarding feeding, resting, and walking activities. We focused on these devices because we believe they are more easily usable in extensive small ruminant farms.

2. Materials and Methods

A literature analysis was carried out to evaluate the current state of the PLF and the new technologies that can be adapted to the extensive farming system. It identified the PLF systems, innovative technologies, and automation currently available and under development for small ruminants.

We followed some indications from Jiang et al. [36] to choose the period to analyse. From 1973 to 2024, the number of PLF publications grew. Still, three phases can be identified according to different fields of interest: the germination phase (1973–1996), the exploration phase (1997–2016), and the rapid development phase (2017–2024). The first phase involved understanding information technology with particular attention to milking and oestrus detection. The exploration phase focused on animal health and welfare concerning diseases transmissible to humans and informatics optimisation. From 2017 to 2024, researchers showed increasing interest in artificial intelligence applications in livestock breeding, leading to a rapid development phase of PLF with 3000 publications. Our research was based on studies carried out in the rapid development period, during which the interest in applying technologies to small ruminants increased [15,37]. The search was conducted on Google Scholar and Scopus, focusing on studies carried out in the last 7 years (i.e., 2018–2024) and evaluating the cutting-edge application of PLF in extensive livestock systems. The following keywords were combined for the search: (i) "Precision Livestock Farming or PLF", "sheep or ewes" and "goat", and "small ruminant"; (ii) "PLF", "extensive system", "grazing"; (iii) "PLF", "technology", "camera-based", "audio analysis", "RFID", "GPS", "GIS", "collars", "data logger", "virtual fence or VF", and "IoT". Over 120 articles were identified for the indicated words. Articles concerning precision diagnosis, advanced bacteriological and parasitological diagnostics, and precision medicine were excluded from the evaluation process. To draft the review, 81 articles were considered.

3. Results

3.1. Precision Livestock Farming in Extensive Small Ruminant Farming

Small ruminant farms are numerous and very varied (in terms of using sheep or goats, local breeds, and different production purposes and degrees of intensification). However, they all contribute to maintaining natural habitats and biodiversity [15]. To increase profit margins, according to market demands, farmers are abandoning traditional small ruminant farming and moving towards more specialised extensive forms (all-grass or organic lambs; fine wool) or intensive production systems (dairy sheep and goats) [23]. In both systems, there is a labour shortage and a low presence of young people in the small ruminant sector. Extensive systems, which cover a lot of global agricultural land, have significant socio-economic importance worldwide for maintaining ecosystem services. Therefore, the application of technologies in management could solve some problems. Precision Livestock Farming in extensive animal farms includes wearable sensors, environmental monitoring equipment, and remote sensing, which can monitor production, solve management problems, and improve efficiency in resource management and decision-making processes [19,23]. Over time, most farmers have shown a greater interest in technologies, adopting systems adapted to their needs, such as mechanical milking, electric fencing, and solar panels [22,38,39]. They seem to appreciate technologies that interfere less with consolidated routines and that they can take care of and manage autonomously [6,40]. However, precision farming systems and new technologies require acquiring new skills (technical, IT, and data management skills) and, therefore, the presence of specialised technicians to follow farmers. Technological applications in intensive systems of small ruminants have reduced labour and increased production, as noted in previous research [16,37] on the use of electronic identification (EID) systems for semi-automatic milk registration in goats and sheep. As reported by [39] Bernabucci et al. [6,41], little information is available on extensive systems. Until 2018, there were not many articles published per year. There was a peak in 2019 (with 59 articles). Their results show that significant publications on precision farming in extensive systems come from Europe, with Asia ranking second due to Europe's greater research capacity and financial resources. From the bibliography analysis, the sheep is the species of concern that has been raised extensively. Research regarding extensive breeding has been recorded recently for cattle and small ruminants on pasture [6,37,39–41]. The term "behavior" applies to cattle since behaviour control is fundamental for precision systems. Sheep farming is of particular interest for milk and meat production. Studies on animal behaviour have used wearable sensors, and the activities monitored have mainly been eating, grazing, resting, stationary behaviour, standing, walking, trotting, running, and scratching [30,42]. The study of behaviour has also involved grazing animals, as reported by Bunyaga et al. [43], with attention to feeding activities and standing or walking with heads down. Observing behaviour is a valid tool for the rational use of pasture and the correct satisfaction of the nutritional needs of small ruminants [7] as it is also helpful for identifying states of animal distress such as lameness. Sensors monitoring an animal's behaviour reduce the need for the visual observation of animals [42], allowing for obtaining information on stress, diseases, lameness and daily feed consumption [44]. Mao et al. [33] reported that walking and scratching were grouped as active behaviours while standing and resting were grouped as inactive behaviours to detect potential diseases. Nóbrega et al. [42] observed, after pre-processing the data collected by a customer of iFarmtec, the existence of an unbalanced dataset as a result of the natural behaviour of sheep that naturally feed/eat for long periods, with the remaining states mainly transient. Evidence has shown that reduced activity levels in animals and increased rest levels can be signs of disease, pain, or heat stress [5]. Below are the main results achieved by applying innovative technologies in extensive systems of small ruminants. Tables 1 and 2 synthesise the technology and application fields associated with wearable and non-wearable sensors examined in the recent literature that can be used in small ruminant farming.

Table 1. Main types of wearable sensors.

Device	Position	Application	Technology	Recorded Parameters	References
Electronic animal identification	Ear tag Ruminal bolus Injectable transponder	Sorting gate, feeder, mating	Radio frequency	Individual data	[4,6,24,45]
GPS and localisation	Collar	Virtual fence, localisation, grazing	Satellite net-work	Location	[16,29,42,43,46,47]
Sensors to measure physiological activity: Temperature	Ear tag Bolus Injectable transponder	Health (fever), stress, heat, drinking	Thermistor	Rectal, rumen, or vaginal temperature	[4,5,7,48–50]
Sensors to measure physiological activity: pH	Bolus	Stress sensor data	Rumen pH		[37,51]
Sensors to measure behaviour	Ear tag Bolus Collar Pedometer Harness	Grazing behaviour, localisation	Triaxial piezoelectric, accelerometer, jaw-movement recording system	Behaviour, feeding, rest, rumination, lameness, behaviour during parturition, mating	[7,32,42,44,52–61]
Virtual fencing technology	Collars with position, acoustic and electrical stimuli	Collars with position, acoustic and electrical stimuli	Coordinates and GPS or satellite signals or by a ground cable that communicates with the collars	livestock management for welfare monitoring, pasture management	[15,24,27,28,62–64]
Network technologies	Collars with accelerometers and position sensors;	Sensor nodes with data storage and processing capabilities, gateway, web server, algorithm	IoT, big data, and machine learning (ML) technologies	livestock management for welfare monitoring, and pasture management	[52,65,66]

Table 2. Main non-wearable sensors and network technologies.

Device	Position	Application	Technology	Recorded parameters	References
Camera	fixed in the stable or in the field	handheld or fixed camera	Optical image	Posture	[67]
Camera coupled with remote sensing techniques	mounted on remotely controlled drones	fixed camera	Optical, infrared	Behaviour, growth, supervision, body condition, and pasture biomass	[30,42]
GPS devices coupled with remote sensing techniques	mounted on remotely controlled camera	Collar with GPS device; handheld or fixed camera	Satellite network; LiDAR or multispectral camera; ultrawideband real-time tracking system (UWB RTLS)	Behaviour, supervision, pasture biomass, position, and a more accurate evaluation	[43,64,68–71]
Wireless (WSN) technologies	sensor nodes with data storage and processing capabilities	sensor nodes with data storage and processing capabilities	Transceiver, sensors, microcontrollers, and energy sources	monitoring grazing livestock, and their activity in real time using Wi-Fi	[16,46,59,72]

3.2. Wearable Sensors

According to their physical relationships to the animals, PLF sensors are commonly categorized as wearable and non-wearable. Some sensors are applied directly on the individual animal and can provide information in real time or via data loggers downloading in key passages. The translation of data collected from sensors (movement, body position, temperature, etc.) into physiologic status form such as ovulation or lameness is relevant for farm management. In the case of extensive systems, these sensors provide useful information related to the grazing and resting behaviours of the flock. Wearable and portable devices are among the most widely used systems in precision animal husbandry. These systems have small features and can be placed on animals to provide relevant information on each animal continuously and in real time. Wearable devices are also called "portable" as they are non-invasive sensors that can be put on and taken off without the need for veterinary assistance or specialized equipment or tools. However, a small percentage of portable devices, such as subcutaneous implants, are not considered wearable sensors [14]. For the optimal operation of these devices, a strategic position in the breeding environment is necessary. The choice of sensor or device to be used and its position depend on the technology, the type of breeding, the environmental conditions, and the characteristics of the animals [56,59,61]. Recently, there has been much research on sensors used to detect behaviours such as position changes, temperature changes, resting, grazing, or rumination in small ruminants [50,52,64,65].

3.2.1. Electronic Animal Identification

Electronic identification (EID) systems are a mandatory technological component under EU laws (Official Journal of the European Union, 9.1. 2004) [73]. The registration of goats and sheep born in 2010 or later with electronic identification has received considerable attention. Depending on the application, the sensors for small ruminants' identification can be found in ear tags, ruminal boluses, or injected chips under the skin [19]. Electronic identification systems allow each animal to be identified and data to be stored and updated for various decision-making processes [25]. Passive EID tags are small and rely on storing an information code and a copper coil that briefly charges the transmitter through energy transmitted by an active reader [4,24]. According to EU legislation, using EIDs is mandatory for sheep and goat species. It represents an opportunity to introduce the PLF system in extensive management systems. Radio frequency identification (RFID) systems operate on different radio frequency levels, which determine their transition distance and ability to pass materials (noise to signal ratio): low frequency (LF, 125–134.2 kHz), high frequency (HF, 13.56 MHz), and ultra-high frequency (UHF, 860 MHz in the EU or 915 MHz in the US). According to Cappai et al. [45], advanced technologies for animal identification and production monitoring based on RFID may also be a valid tool for individual ewes' health and welfare problem-solving. In the case of extensive livestock farming, real-time identification and monitoring are essential to control herds. Morrone et al. [19] have reported an accuracy of around 96% using GPS sensors and drones.

3.2.2. GPS and Localisation

The Global Positioning System (GPS) relies on radio signals from specialised satellites that are available during the positioning. GPSs provide data on animal movement and spatial distribution in pastures, including for small ruminants. The animal locations are often combined with relevant environmental information, such as on the vegetation type, topography, proximity to water, and distance to human activities and infrastructures, to evaluate the habitat selection of animals [4,62,63]. Monitoring livestock behaviour in extensive grazing systems can assist in managing the animal and its interactions with the environment [48]. Currently, the devices are attached to a collar around the sheep's neck, similar to the bells traditionally used in Alpine farming [16]. Decandia et al. [67] reported that GPS sensors on the collar rather than near the mouth and nape position had a low error in the position assignment. This result is positive from the point of view of animal welfare as sheep are grazed, especially on extensive farms, and are accustomed to using leather collars with hanging bells. With a variable weight depending on the manufacturing companies, the tracking technique can be considered non-invasive as it does not influence the natural behaviour of sheep and goats. However, usage is scaled based on the presence of energy: battery life in the field, the lack of wireless data transmission, and the accuracy, interpretation, and contribution of these measurements to decision-making [74]. Some devices have a GPS sensor and a small solar panel for charging the battery. The operation involves the transmission of positions at different intervals depending on the battery charge, with a margin of error. The datasets are analysed using geographic information software. Knowledge of the positions of the paths taken by grazing animals allows one to evaluate an animal's circadian rhythm, assessing whether movement patterns are regular or change over time. It allows one to identify the preferred area on the pasture based on the stopover time and the calving sites and determine when calving begins and whether the offspring survive in the first days after birth [25]. GPS technology also facilitates the study of animal interactions to help determine whether a pasture is overutilised and how access to high or low-quality pasture impacts sheep group dynamics [16,42]. By combining GPS tracker technology with a long-range wide area network (LoRa-WAN), it is possible to monitor the locations and movements of animals over extensive pastures [9]. The use of RFID proximity collars has been shown to be an efficient way to monitor a large group of animals at a reasonable cost. Bunyaga et al. [43] observed sheep in New Zealand using sensors that logged animal positions; di Virgilio et al. [29] studied three Merino sheep in Patagonia, Chile, equipped with head-mounted 3D activity meters with GPS receivers. Overall, these GPS studies showed that purely positional information about a grazing animal is important for assessing its welfare [46]. Ren et al. [71] showed that the combination of various technologies (infrared cameras, 3D computer vision, and GPS) yields good results in monitoring the position and behaviour of small ruminants with high accuracy. In other studies, GPS collars [75], combined with machine learning [18] or accelerometers and weather stations [54], have been used to detect lambing events, with an accuracy of up to 91%.

3.2.3. Sensors to Measure Physiological Activity

Sheep exposed to high ambient temperatures experience heat stress, and their homeostasis, reproductive function, and performance are compromised. Body temperature is a reliable measure of heat stress and, hence, a good indicator of an animal's health and well-being, reflecting the physiological activity of the animal body [5,6]. Non-invasive temperature-sensing technologies have made substantial progress over the past decade. Types of measuring devices, such as surgical devices, have been developed: implanted devices, infrared devices, and intraluminal boluses equipped with temperature sensors [7,48]. Fuchs et al. [49] monitored the body temperature and heart rate of domestic sheep grazing freely on unfenced mountain pastures with surgically implanted devices. Moreover, subcutaneously implanted sensors could provide reliable measurements for heart rate and body temperature, two indicators that can be used for the early detection of diseases and stress. Instead, caudal data loggers programmed to record temperature could also be applied for lambing time identification in sheep [50]. Such systems require an accessible transmission network. Sensors inside ear tags are unreliable and less commonly used [4]. Rumen boluses sense changes in the ruminal microflora for temperature and pH parameters, which are used to monitor rumen conditions. Furthermore, pasture access and composition changes can be detected if they influence the reticulum pH [51]. Sensors for recording heart rate or ECG are currently used only in the research field because, to become commercial, they require an accurate and constant transfer of data and algorithms that can simultaneously transform and process the data [6]. Bordignon et al. [8] reported using a multisensor (accelerometer, magnetometer, temperature sensor, and GPS) tag to assess feeding patterns, energy expenditure, and environmental factors. Horie et al. [76] examined the effects of climatic conditions on the grazing behaviour of Mongolian sheep. Through studies about eating, ruminating, standing, and lying behaviours, machine learning algorithms can achieve classification accuracy rates ranging from over 70% using motion sensors embedded in collars [77].

Marsden et al., 2021 [78] used collar multisensors to estimate urination volume, considering the ewe's squatting time from accelerometer data.

3.2.4. Sensors to Measure Behaviour

Sensors play an essential role in PLF technology by gathering real-time data across various aspects of livestock production including animal behaviour, health status, and environmental conditions [3]. In particular, they can record movement and resting patterns, feeding behaviour, and social interactions between animals and thus observe animal behaviour. These sensors can also provide valuable information about the health statuses of the animals as they record vital signs such as the body temperature, heart rate, respiratory rate, and activity levels to detect signs of illness or stress. Monitoring animal behaviour facilitates the collection of information related to farm management such as heat, childbirth, rumination, illnesses, or relationship problems. Commercially available sensors are accelerometers, usually placed on the neck or paws, or in-ear tags or boluses. Depending on where the sensor is located, different behaviours can be correlated to the accelerometer signals, and, therefore, the behaviours can be quantified. Several studies have been conducted to classify cattle behaviour compared to sheep behaviour [25,42]. Eating, grazing, stationary, walking, running, active behaviour (walking and scratching), and inactive behaviour (standing and resting) have been studied. More complex behaviours, such as rumination, kicking and foot movements, grazing, standing, walking, lying down, and running, have been successfully classified using accelerometers [33]. Sensors attached to the animal's neck or ear often provide information only on activity, i.e., the total amount of movement [44]. The sensors applied around the animal's paws can also provide information on the number of steps and rest times [44]. Almasi et al. [45] demonstrated that accelerometers can indicate variation in behaviours among grazing sheep: in their study, most of the sheep's time was spent grazing, ruminating, and idling while smaller amounts of time were spent walking, licking, and in other behaviours, and the time spent by an animal in each activity varied during the day. Males and females showed differences in the time spent grazing. Monteiro et al. [36] reported that they could provide information on rumination time, the number of chewing movements, and feed and water intake. Accelerometers were also tested to evaluate their ability to discriminate between sheep's biting and chewing activities during grazing [52]. Plaza et al. [59] showed that the spatial distribution of grazing Churra sheep was non-random because the animals seemed to develop common behavioural patterns. Notably, airborne data related to vegetation height, slope, and aspect showed the most significant effect on the location of sheep grazing. Moreover, sheep chose the grazing areas that offered the freshest and most nutritious food. The application of the 3D accelerometer technology has proven to be very useful in the rationalisation of reproductive aspects, such as in the onset of parturition [49–51], in identifying behavioural changes in ewes during parturition [43], or in the estimation of the serving capacity of rams [48]. Sensor systems can detect infectious diseases, metabolic disorders, and lameness [46,65]. Many conditions can also be detected earlier than through manual monitoring, even before the appearance of clinical signs, with the analysis of data collected and the results of the processing software connected to the farmer's smartphone [59]. Data transmission and energy supply limitations are the main obstacles to using sensor-assisted monitoring in extensive and remote rangelands. Accelerometers record a lot of data, but with difficulty in analysis and interpretation, they require suitable algorithms for data processing [37,79].

3.2.5. Virtual Fencing

Virtual fencing (VF) technology is an innovative method for extensive animal management that replaces physical barriers with electronically placed boundaries. Animals are prevented from passage by a system of visible and/or audible cues combined with an electric stimulus: when the animal approaches the virtual fence, the collar emits a warning signal, usually a sound. A painful but harmless electric shock is given if the animal moves forward and is about to cross the fence line. Recent studies have shown that animal welfare in virtual fences is comparable to that in a physical electric fence and that cattle and sheep can learn to respond to audio signals and avoid electrical impulses [24,28]. The position of the virtual border can be defined by coordinates, GPS, or satellite signals or by a ground cable that communicates with the collars. The main species were tested in different virtual fencing systems: cattle [26,28], sheep [27,62,63], and goats [15]. Studies have demonstrated different responses in species and with varying systems of monitoring [64]. The multiple animal monitoring capabilities allowed by VF collars (rest time, distance travelled, and spatial distribution) represent a further key advantage of this technology, highlighting the potential of precision breeding (Table 1). Hamidi et al. [64] have shown that the application of VF collars and other sensors for monitoring grazing animals provides precise position indications, and by monitoring grazing from above using Unmanned Aerial Vehicle (UVA) technology, it is possible to improve grazing systems, as it predicts the biomass changes across animal data. Aaser et al. [28] tested the use of the Nofence© system to keep a group of Angus cattle (Bos taurus) inside a virtual fence with minimal welfare implications, i.e., without harming livestock welfare, basic health, and functioning. Eftang et al. [27] demonstrated that sheep could quickly associate audio cues with the electrical stimulus, and the ewes efficiently adapted to a second virtual boundary, indicating that they generalized their experiences from the first to the second boundary. These findings are important for animal welfare, as noted in the heart rate response to the electric stimulus, indicating a brief stress reaction. The sheep species adapts easily to the audio signal, as reported by Marini et al. [62], and can learn to associate the sound signal with the electric shock and, therefore, after a learning period, at least in some cases, will remain on one side of the virtual fence. Marini et al. [63] managed to keep a group of sheep in a virtual pen for five days. However, several studies have reported that some animals cross the virtual border. A word cloud of the primary wearable devices and applications in sheep extensive farming systems is shown in Figure 1.

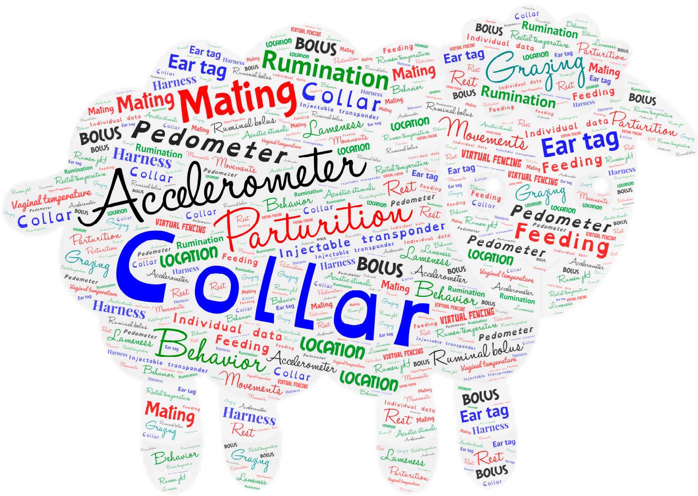

Figure 1. Word cloud of the main wearable devices and their applications in sheep extensive farming systems (in blue and black are shown the device positions; in red and green are shown the recorded parameters).

The font sizes of individual words correlate positively with the number of searches on each specific device.

3.3. Non-Wearable Sensors and Network Technologies

Animal observation can also be carried out with fixed cameras that provide images or videos. This technological equipment facilitates the ability of farmers to watch and monitor many parameters within the barn, including temperature, activity levels, sound levels (such as vocalisations, sneezing, and coughing), and specific behaviours. For intensive indoor livestock farming, fixed cameras are used; for outdoor farming and grazing animals, fixed cameras are often integrated or replaced with cameras mounted on remotely controlled drones for large-scale surveillance [6]. Cameras can be cost-effective alternatives to positioning sensor collars, which are expensive and must be fitted to large numbers of animals for surveillance to provide helpful information [67]. Another possibility for monitoring livestock with new technologies is the use of drones. Caja et al. [15] have reported using drones that include thermal cameras in small ruminant farming. The drones also provide landscape overviews, useful for assessing pasture biomass and grazing intensity [6]. However, evaluating drone images can be a time-consuming manual task. The observation of animals and social interactions is facilitated with cameras and with better results when combined with other technologies. The effect of drones on the behaviours and well-being of domestic grazing animals requires further investigation. Using drones equipped with cameras for counting and studying animals in the landscape is increasingly widespread, especially for wildlife [30]. Another type of camera is the thermal camera, which measures the amount of infrared radiation (heat) emitted by the body surface of an animal and can distinguish animals in the dark, making it possible to monitor them at night [42]. In the case of drones with thermal cameras, light, shadow, or dense vegetation conditions are less of a problem than for drones with cameras. In extensive systems, some studies have demonstrated the possibility of monitoring livestock with GPS devices coupled with remote sensing techniques such as LiDAR [68] or multispectral technology [64,69,70]. These systems have reported very interesting results for quantifying the environmental characteristics and explaining the movements of grazing animals [43]. As reported by Ren et al. [71], the combination of a multi-camera video recording system for detecting sheep behaviours in standing and lying positions with an ultrawideband real-time tracking system (UWB RTLS) provides a position and a more accurate evaluation. In agriculture and animal husbandry, the application of wireless (WSN) technologies, consisting of a transceiver, sensors, microcontrollers, and energy sources, is increasing. The network comprises sensor nodes with data storage and processing capabilities, which, unlike RFID systems, can communicate wirelessly [16,72]. Sensor network applications have become more important in recent years, partly due to the development of small, low-cost, multifunctional sensor nodes with low power consumption, helpful in monitoring grazing livestock. Several studies have reported positive results for using an inexpensive and relatively simple WSN system to track livestock and monitor their activity in real time using Wi-Fi [59]. The system records the animal movements using accelerometers and position sensors [80,81]. All information about the animal's identity, location, and activity is sent to a base station node, which forwards it for storage on a web server. However, in several technologically well-developed countries, broadband in the countryside is still absent [46]. The recent and unprecedented evolution of IoT, big data, and machine learning (ML) technologies has created opportunities to recover additional and valuable information from grazing systems. ML techniques are increasingly used in livestock management for welfare monitoring and pasture management [65,66]. In the IoT system, collars constitute the main data collection interface, responsible for supervising behaviour and location. The posture control algorithm is executed locally, analysing and applying corrective stimuli (e.g., electrostatic and auditory signals). Subsequently, user-relevant data are transmitted to an infrastructure network of fixed beacons [47]. These devices, installed according to the intended grazing areas, implement periodic and synchronised signal emission throughout the network, allowing the collars to evaluate their position through RSSI-based localisation techniques. The Gateway is an aggregator element that communicates with all beacons and connects to the local internet network via broadband. The data are collected on data structures without the internet and sent to a cloud platform. As reported by Goncalves et al. [52], this project is one of the first developed in a functional way for the sheep species, collecting information regarding the sheep's posture, location, and infractions. The main non-wearable devices and applications in sheep extensive farming systems are shown in Table 2.

Recent PLF solutions provide essential information that supports farmers' decision-making to monitor the welfare of small ruminants at a pasture. The technologies presented include non-wearable and new sensors, highlighting that they all have different strengths and weaknesses, especially when applied to the pasture-based sheep farming system (Table 3). Indeed, some systems provide excellent utility for grazing animals by providing real-time information on location, behaviour, health, and social status. However, most of the devices available for sheep have not yet been validated, therefore providing less robust and accurate data. For other systems, the purchase cost is too high, or the farms are located in areas without internet connection. Advances in computer science, electronic engineering, and artificial intelligence are the bases for efficiently and automatically monitoring animal activities and welfare.

Table 3. Strengths and weakness of sensors and network technologies.

Device	Position	Positive Aspects	Negative Aspects	References
Camera	fixed in the stable or in the field	Easy installation and data acquisition	Need to adapt structures to eliminate obstacles; limited use on pasture	[67]
Camera coupled with remote sensing techniques	mounted on remotely controlled drones	Useful for extensive farming	Evaluating drone images can be a time-consuming manual task	[30,42]
GPS devices coupled with remote sensing techniques	mounted on remotely controlled camera	Useful for extensive farming; GPS collars are readily available on the market; real-time location and health status of the animal can be recorded	GPS collars' costs to equip every animal make them unsuitable for wide deployment on small ruminant farms; farmers' inability to manage the drone; internet connection difficulties; the algorithms for automatic detection of animals and/or the characterisation of their behaviours are only at the research stage	[37,47,64]
Wireless (WSN) technologies	sensor nodes with data storage and processing capabilities	Useful for extensive farming	Internet connection difficulties	[1,37,59]

4. Discussion

This study represents an approach to the analysis of the Precision Livestock Farming of small ruminants raised with an extensive system. Our results highlight a recent curiosity, since 2021, towards this breeding system, mainly linked to research funded and carried out in Europe, despite it being in last place for the number of small ruminants raised outdoors. Australia represents the first place for small ruminants, the extension of pastures, and the application of PLF [39]. At the farm level, the wearable sensors, the environmental monitoring equipment, and the remote sensing can be widely employed in decision-making processes. Within livestock farming, wearable sensors present consequences due to their characteristics. Their portability brings with it specific problems such as energy management. For their operation, these solutions require electric batteries to provide continuous energy sources for data collection. In many cases, an interruption of animal monitoring is necessary for recharging [12]. Tzanidakis et al. [7] reported that the diffusion of PLF tools is held back by producing extensive data whose collection requires large storage devices or cloud services that are still little-used [45]. Among the technological advances related to PLF, big data and advanced analysis capabilities are highlighted [39]. Small ruminants are of great importance in fighting the climate emergency. The distribution of sheep is throughout the national territory but primarily concentrated in southern Italy and Sardinia. Evaluations made with sensors and visual observations have shown that the breeds of southern Italy are better adapted to the climate. Therefore, using reliable sensors to measure physiological and environmental parameters, combined with intelligent methods, can help monitor climate change [9,21,39]. Adopting automated technologies for monitoring heat stress, such as indwelling probes, intraruminal boluses, thermography and implantable devices, can provide real-time data on body temperature and take timely measures to mitigate its effects [48]. The use of GPS collars, accelerometers, the IoT, and other devices allows for the identification of subjects in heat stress [48], with parasitosis [16], and in environmental stress [47]. It is possible to identify energy expenditure and the adaptation strategy based on the distances travelled [31]. Bernabucci et al. [39] have reported that monitoring techniques with remote sensing promote connectivity along the animal supply chain, promoting sustainability and food security. For example, the estimation of the quantity and quality of pasture, which is essential to guarantee nutritional needs and livestock productivity in extensive livestock systems, is measured by conservative technologies such as drones and vegetative indices [31]. However, it could be improved by using artificial intelligence and specific models, optimising resources, reducing excess food supplements, and allowing the conservation of grass cover. Moreover, from an economic point of view, the diffusion of PLF in rural communities could promote the development of new professions and specialisations.

5. Conclusions

The introduction of PLF technologies in extensive livestock farming can provide real-time results on the conditions of grazing animals [8,19] and their interaction with climate change [9]. Greenhouse gas emissions and water shortages can be addressed by applying PLF to detect temperature, type of feeding and water consumption [21]. However, some technologies have limitations, such as the batteries of collars, signal reception, data accumulation and processing, and results on the behaviour and health statuses of animals in the long term [22,23]. Invasive devices can cause discomfort, negatively affecting animal well-being and altering the behaviours intended to be monitored, leading to an increased focus on contactless technologies [33]. In this context, image analysis seems to be the most promising technique for monitoring pigs and poultry while wearable sensors, although available, are less interesting for practical applications. The adoption of new technologies is hampered by several factors, including the level of management required for implementation, structural constraints for installation, lack of knowledge of farmers, and different levels of interest in specific technologies. Smart technologies can facilitate more informed choices for the farmer and the consumer [8]. However, such technologies produce a large amount of data, which must be stored securely, easily analysed, and accessible to the user. Therefore, further efforts are needed to develop secure and accurate data storage systems, optimised data compression algorithms, and integrated long-term storage solutions. In this context, the future use of artificial intelligence tools offers prospects for advanced data processing, greater control over sensor input data, and improved decision-making. However, data privacy raises ownership, property rights, and use issues. High costs and the expertise required currently limit the development of such technologies. Access to the latest technologies may remain limited to large and industrialised farms. The digitalisation of agriculture could further influence job opportunities and job profiles in the sector. Therefore, animal husbandry, agronomy and data analysis should be deepened and combined to develop complete PLF solutions [19,22,24]. Although sheep and goat farming in Italy constitutes a modest fraction, from the point of view of the cultural, social, and environmental economies, breeding small ruminants is fundamental, particularly in the maintenance and protection of unproductive territories. Efficient livestock management is essential in extensive farming systems to increase environmental sustainability and ensure easy farm management. The extensive farming of small ruminants has significant disadvantages including predation by wild animals, high variability in agrometeorological conditions, staff shortages, low investment in innovation, a lack of efficient breeding programs, and on-farm technical support. Automated animal monitoring based on grazing sensors and drones offers excellent potential to improve animal welfare as it can capture animal physiology, behaviour, and environmental factors in real time. These solutions can enhance and support the farmer in the decision-making process by allowing the automation of several tasks that conventionally rely on human effort or supervision and by increasing the amount of available information, which can then be used to manage the resources more effectively. Information and Communication Technologies (ICTs) are regarded as key tools to improve livestock exploration efficiency, collecting relevant information about grazing animals, such as on preferred grazing areas; allowing the better management of pastures; detecting activity patterns directly associated with the animal's well-being; or even detecting attacks from predators.

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