

## Review / Derleme

# Precision livestock farming technologies: Novel direction of information flow

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**Abstract:** Precision livestock farming (PLF) is a digital management system that continuously measures the production, reproduction, health and welfare of animals and environmental impacts of the herd by using information and communication technologies (ICT) and controls all stages of the production process. In conventional livestock management, decisions are mostly based on the appraisal, judgment, and experience of the farmer, veterinarian, and workers. The increasing demand for production and the number of animals makes it difficult for humans to keep track of animals. It is clear that a person is not able to continuously watch the animals 24 hours a day to receive reliable audio-visual data for management. Recent technologies already changed the information flow from animal to human, which helps people to collect reliable information and transform it into an operational decision-making process (eg reproduction management or calving surveillance). Today, livestock farming must combine requirements for a transparent food supply chain, animal welfare, health, and ethics as a traceable-sustainable model by obtaining and processing reliable data using novel technologies. This review provides preliminary information on the advances in ICT for livestock management.

**Keywords:** Internet of things, livestock data management monitoring tools, precision livestock farming, health, welfare.

## Hassas hayvancılık teknolojileri: Bilgi akışının yeni yönü

**Özet:** Hassas hayvancılık (PLF), bilgi ve iletişim teknolojilerini (ICT) kullanarak hayvanların üretimini, üremesini, sağlığını ve refahını ve sürünün çevresel etkilerini sürekli olarak ölçen ve üretim sürecinin tüm aşamalarını kontrol eden dijital bir yönetim sistemidir. Geleneksel hayvancılık yönetiminde kararlar çoğunlukla çiftçinin, veterinerin ve işçilerin değerlendirmesine, muhakemesine ve deneyimine dayanmaktadır. Üretime yönelik artan talep ve hayvan sayısı, insanların hayvanları takip etmesini giderek zorlaştırmaktadır. Bir kişinin, yönetim için güvenilir görsel-ışitsel veriler almak için günde 24 saat sürekli olarak hayvanları izleyemeyeceği ise açıktır. Son teknolojilerle bu bilgi akışı hayvandan insana olarak değişmiş ve bu da toplanılan güvenilir bilgilerin, operasyonel ve efektif olarak bir karar alma sürecine dönüştürmesine (örn. Üreme yönetimi veya buzağılama takibi) yardımcı olmuştur. Günümüzde hayvancılık, yeni teknolojileri kullanarak güvenilir verileri elde ederek ve işleyerek izlenebilir ve sürdürülebilir bir model olarak şeffaf bir gıda tedarik zinciri, hayvan refahı, sağlık ve etik gerekliliklerini birleştirmektedir. Bu yayında, hayvancılık veri yönetiminde kullanılan bilgi ve iletişim teknolojileri alanındaki gelişmeler hakkında güncel bilgiler derlenmiştir.

**Anahtar sözcükler:** Hassas hayvancılık, hayvancılık veri yönetimi, izleme araçları, nesnelerin interneti.

## Introduction

“Man goes to nature to learn what nature is, but, in so doing, he introduces possibilities of distortion through his own presence.” –

T.C. Schneirla (154)

Before the industrial revolution 4.0, livestock management decisions were mostly based on the observation, judgment and experience of a human. The last decade has seen a great metamorphosis and brought a novel concept named “Precision livestock farming

(PLF)”, which is a digital management system that periodically or continuously measures production, reproduction, health and welfare of animals and environmental impacts of the herd through a “per animal” approach by using monitoring tools, mainly the internet of things (IoT), and controls all stages of the production process (11, 15). Thus, the use of automated measurement methods to monitor animal behavior has become increasingly widespread, and a number of models have been introduced that can distinguish reasonably accurate traits of daily physiological routines.

Different behavioral monitoring studies implemented on activity (50), eating (30), and milking (6) have created the fundamental infrastructure of PRL. The pioneering study was conducted by Farris, 1954 (50), for the detection of estrus by monitoring the mounting activity and counting the number of steps during estrus. For eating, the initial methodology was investigated in cattle (30) and soon after in sheep (127) by classifying the jaw movements to distinguish bites from chews. These pioneer studies have led to the idea of recording biting and chewing sounds with a wireless microphone attached to the forehead of the animals (103) and thus revealed a simple approach on intake and time per bite, for researchers to focus on classifying jaw movements (biting sounds were louder than chewing with differences in spectral composition) of the grazing process. However, PLF tools are still under adaptation and the evolution of digital technologies varies greatly between different sensor systems and application areas. Therefore, the development of PLF was driven by a number of variables in the care of livestock such as the growth of herd size, and the resulting inability of farmers to care for individual animals, the economic efficiency of farming, and increasingly environmental factors such as many other developments in the fields of agriculture, computing, and engineering. As these variables create more considerable complexity in farmers' work, it has become necessary for farmers to be able to monitor variables related to basic livestock production processes (11). The elementary principles for the emergence of PLF tools is to provide accurate and relevant information to take decision to a farmer (60). These incentives resulted from challenges for farmers and provide opportunities for farmers, veterinarians and engineers. PLF is possible due to technological advances, but challenges for local farmers such as animal identification in larger herds, productivity demands, and more recently, sustainability and welfare have offered unique opportunities for innovative technologies to be tested and applied. Therefore, the definition of the PLF technology was that the combination of computer and ICT use to make the production chain more efficient due to the increased control it affords resulting in improvement in animal welfare and benefits the best in using the resources resulting in decreased environmental pollution (13). The introduction of process control procedures has resulted in significant improvements in other industries (181).

PLF is a management system, which use sophisticated intelligent software's and systems to combine variety of data from different sources of hardware's for monitoring. This data driven system enables improved health, welfare and production along with minimized undesirable environmental impact through complex monitoring mechanisms such as tele-surveillance.

### Overview of the Existing Tools

Overview of tools for precision livestock farming are considered at the levels of collection and management of data gathered by monitoring using different technologies.

**Monitoring devices:** Many researches were conducted to discover the potential implementation and validation of monitoring systems, while these systems are constantly developing. Behavioral and physiological monitoring of animal variables can be complicated as the method used to collect the data may change and there will always be interindividual variabilities. In order to monitor animal variables several technologies were adopted including image and sound analysis using cameras, sensors or other devices including water/feed consumption, scales etc. For image analysis, as the devices are not required to be placed on the animal no extra stress is produced; while in the prediction stage, it is difficult to retain good precision as the developed software for target tracking and extraction of animal foreground depends on various complicated image factors. Image analyses are used for weight and body condition score estimation, water/feed intake, assessing the gait and lameness along with detection of marked animals in estrus behavior monitoring. At the current state, mainly electronic wearables such as active smart ear tags which receive data from individual animals such as temperature and activity/ingestion patterns; neck and leg collars for rumination and activity loggers and other sensors used for prediction of diseases are widely used alone or in combination with robotic milkers, automatic feeders and inline milk sensors. In some farming, both image and sensing monitoring devices are combined to receive maximal efficiency and data (121). Selected biosensor based monitoring devices according to the system used, feed follow-up, monitoring of behaviour, biological parameters and applied area are listed in Figure 1.

With the increasing number of available sensing tools, a vast amount of generated data is expected to be processed and analyzed where the internet of things (IoT) is the major system for monitoring and data collection. A list of current commercial PLF tools to monitor and support cow health and performance, that includes over 100 tools is accessible by farmers and it is being updated regularly (4D4F Technology Warehouse).

### The Internet of Things

Data obtained by the monitoring tools are connected through various technologies including Machine-to-Machine (M2M) communications, Cyber-Physical-Systems (CPS) Web-of-Things (WoT) and Internet-of-things (IoT). As a part of IoT, communication between machines and devices are mainly attributed as M2M where cloud computing infrastructures are available using telecommunication services (4G, 4.5 G, 5G, satellite). On the other hand, IoT comprises a broader scope of interactions between devices/things/people. CPS systems under IoT comprise physical sensing devices such as biosensors to the digital world. WoT enables the resources using mainstream applications such as HTML, Java, PHP etc. Therefore, IoT allows connecting the data gathered by all the monitoring tools to the internet for improvement of valuing of all livestock related operations (4).

The use of IoT in PLF meets five possible indications classified as surveillance, drug tracking, localization, feed follow-up, monitoring of behavior and/or biological parameters.

**Surveillance:** Animal protein deficit is thought to be the cause of global epidemics. This raises great concerns about disease transmission from animals to humans, making animal health a high priority (41). On the other hand, it is predicted that the demand for meat worldwide will increase by at least 40% in the next 15 years (123), this figure will reach 498 tons in 2050, and the number of animals per farm will increase in response to the demand (43). Consequently, consumer demands such as animal health, welfare and the reduction of antimicrobials use put pressure on veterinarians and farmers.

It is necessary to solve many problems such as monitoring animal health and welfare in the livestock sector, reducing the environmental impact (15% of global CO<sub>2</sub> emission, 1/3 of the arable land and 8% of fresh water) and ensuring the efficiency of the process (43). Today, livestock farming must combine requirements for a transparent food supply chain, animal welfare and health, and an enhanced, traceable and sustainable model. The concept of epidemiologic surveillance system gathers high-quality information in animal health and food safety to make proper decisions and implement actions regarding the prevention of zoonotic disease for public health (world health organizations), animal services (public veterinarians), and private organizations (54).

Practice for the surveillance of animals involves identification and measuring components connected to the animals at least with one tool (For example, ear tags, transponders, accelerometers) wirelessly connected to measure the individual characteristics for specific groups of animals by modern information networks. Analysis for animal disease monitoring and surveillance are usually conducted by epidemiologists; which is crucially important for management of health related issues and risk analysis. Health surveillance is regarded as a tool to monitor the trends in diseases that are of significant economic, trade and security of food importance. Animal disease surveillance includes observing a group of animals strictly to evaluate and focus on a specific condition or disease individually/the whole population with ascertain variations in prevalence and define the frequency and route of epidemic spread. There are also the use of syndromic surveillance systems to detect the vector borne diseases like "Blue Tongue" through the use of pregnancy length and milk yield (108). The above mentioned statement turned into an abbreviation called MOSS (monitoring and surveillance systems) that measures disease and surveillance of animal population (150).

The Moss system includes systematic acquisition, research, analysis, and up-to-date information on health/production / reproductive data for both animal and public health. Public and animal health, as well as monitoring and identification of pandemic diseases of exotic origin such as corona, are among the purposes of

use of surveillance systems. These programs provide guidance in determining effective prevention and control strategies. It also serves to monitor the progress and completion of response programs and to indicate the non-infectious and non-hazardous status of animals and animal-derived products in the animal health field. Ensuring that surveillance plans are on target is ultimately superior (48).

**Drug tracking:** Improved management with PLF allows an increase in the efficacy of drugs used in food-producing animals; as a medication is only used as an adjunct to a good management system bearing responsibilities for public health in livestock. Early detection of individual changes in the health parameters relating to diseases has great importance in early diagnostic interventions as well as successful chemotherapeutic treatment (101). Global misuse of veterinary antimicrobial agents led to an emerging increment in bacterial resistance at an alarming level leading to both human and animal clinical treatment failure. In order to achieve the rational dose regimen of antibiotics for prevention and treatment of diseases along with minimizing the resistance, risk relies on the optimization of pharmacokinetics through assessment and characterization of interindividual variability of drug intake (106). These novel systems therefore not only allow early detection of diseases leading to early drug interventions but also allow the evaluation of the amount of feed and water intake to calculate the exact amount of drug and associate with certain health effects along with transparency/traceability, follow-up of recovering and for refined phenotypes. The future of pharmacokinetic/pharmacodynamics studies are expected to be guided by these smart systems merging the changes in health, welfare, and productive status (65).

**Localization systems:** Localization has crucial importance since the accuracy of the localization affects the cost and the limitations of the system; (33, 78). Indoor positioning systems (IPS) combines sensing and communicating technologies to determine the location of objects/animal in indoor environments (20). Various types of localization techniques are adopted such as Global Navigation Satellite Systems (GNSS), Inertial Navigation Systems (INS), wireless localization and environmental signals (magnetic, air pressure, light, sound) with database matching, dead-reckoning (magnetometer, odometer, inertial sensor based motion sensor), vision sensors (camera, light detection and ranging-LiDAR). These techniques all have advantages and limitations over each other and usually it is difficult to evaluate cost effective high performance localization system; where farm specific solutions are expected to be adopted (102).

The GPS (Global Positioning System) tools are intelligent design to track or find the animals remotely with the valuable aid of GPS tracking collars. This tool determines the exact satellite position by using the global positioning system and updates this information in given intervals. Detected positions are updated regularly or

could be downloaded remotely. The initial technology only allows assessing the obtained data when the detachable collar was accessed directly on-site. However, nowadays innovative technology allows us the acquisition and assessment of reliable data remotely. The collars generally use GSM (The Global System for Mobile Communications) operator signals to receive and typically transmit the specific location. GPS collars use “Geostationary Satellites” to promptly send the precise positioning along with other valuable information to the tracking server or standard PC (35). The above mentioned technology led the dairy farmers to monitor/control their herds effectively at extensive grazing systems in large areas with outdoor positioning systems (8). Tracking animals to find sick or missing individual or drive away predators is time and labor consuming. This day, innovative GPS devices are convenient to track the real-time location of outdoor cattle (166). Feasibly the most significant benefit of GPS trackers obtains the peace of mind they offer dairy farmers (10). On the other hand, indoor positioning systems created different possibilities for the development of tools such as determining the exact position of the cow in heat in large cow herds (148), body condition score (149) determining hot and cold areas in the barn that could adversely affect welfare (131), virtual fence (170), dynamic and smart grazing rotary systems (62).

**Feed follow-up systems:** Monitoring “cattle’s feed intake is considered an excellent tool to form an opinion on their general well-being. Sick cattle will spend time eating less food due to loss of appetite. Thus, rumination

time is becoming a key indicator for health monitoring in that animal regurgitates a bolus of food into her mouth and masticates thereafter. Hereby, when cattle become ill, it eats and ruminates less which allows us to create a rumination chart individually for animal health status. Also, rumination is an important part of the digestive process, and a healthy cow ruminates for 400 to 600 minutes a day, average daily grazing is around 6–10 h per day (179), lactating cows spend around 4.5 h/d eating (range: 2.4–8.5 h/d) and 7 h/d ruminating (range: 2.5–10.5 h/d), with a maximum total chewing time of 16 h/d. The ruminant activity also helps to keep the rumen pH at a level suitable for microbial activity. In the beginning, studies were more focused on pressure sensors mounted on the jaw with a halter (Figure 1) to detect the rumination pattern (30, 88, 185). Then, Burfeind (22) gathered the data and turned it into a monitoring system that can evaluate the data to differentiate the eating and rumination through a computer acquisition system. Today, with rumination activity patterns, the prediction of the feed intake, health status, and environmental impacts is possible. Thus, the difference between healthy and unhealthy conditions like metabolic disorders (ketosis, acidosis, dysplasia, etc.) or stress-caused circumstances (heat stress, estrus, social interactions, etc.) can be monitored. Different types of rumination detections are present (129); such as the movement of neck muscles by ear tag, bolus sensors (66), and/or as wearable sensors (183) for grazing activity, indoor positioning (126), and feed intake with video recording (133) Figure 1.

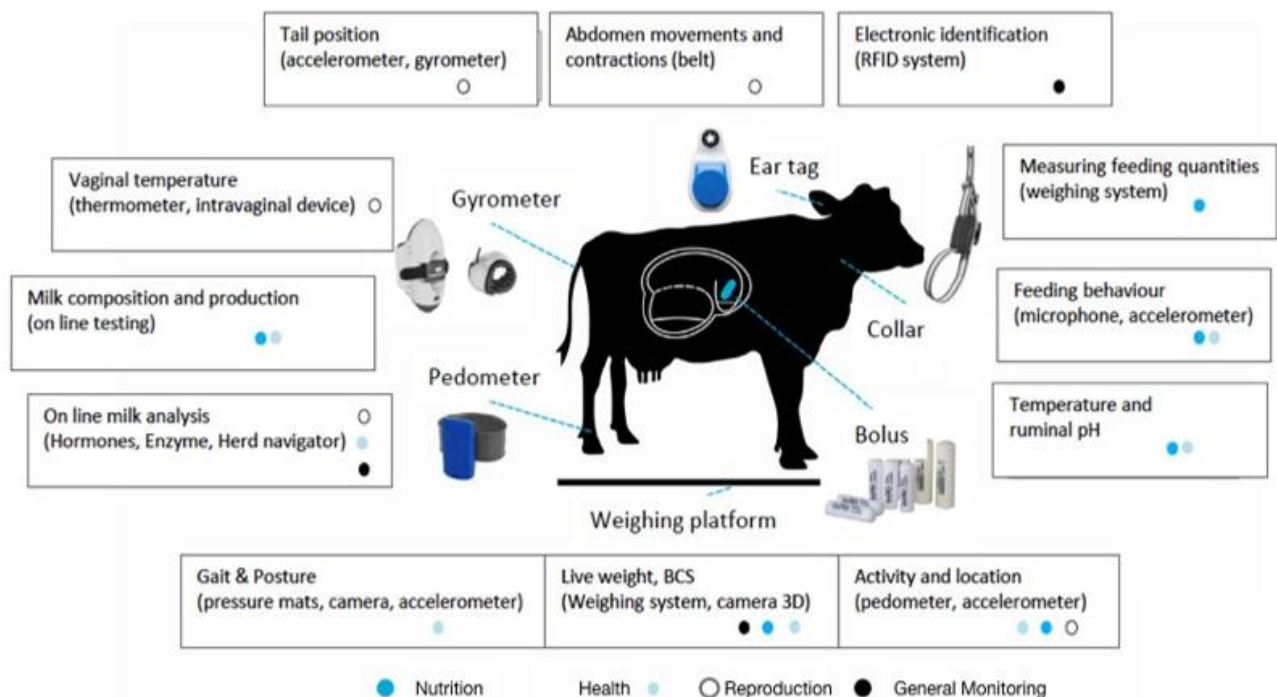
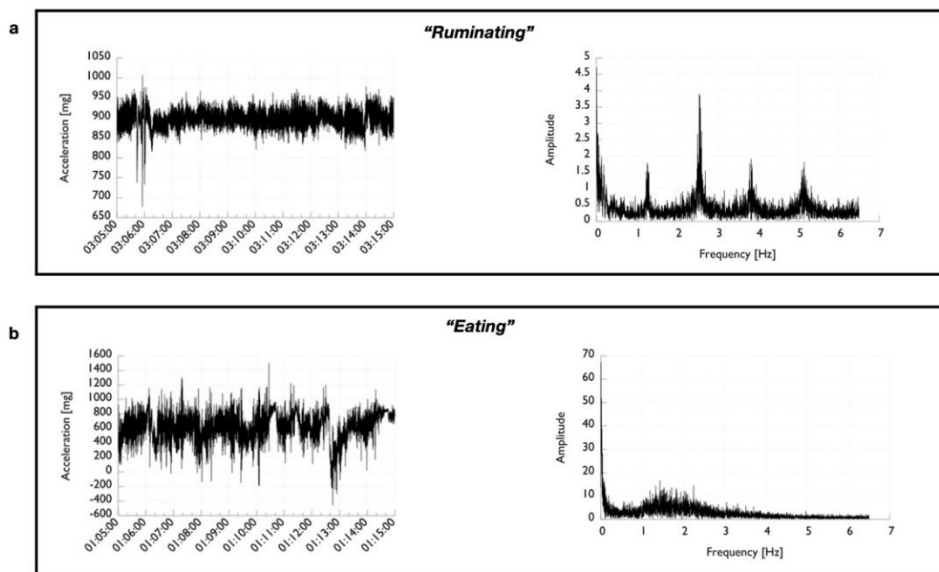
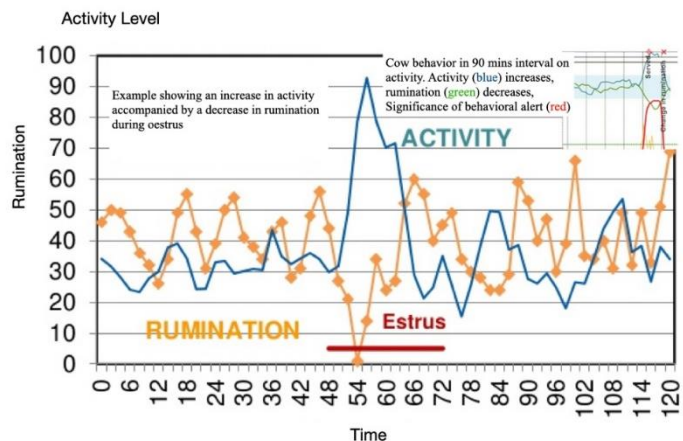


Figure 1. High-Tech Cow (64).



**Figure 2.** Time series representation (left) and corresponding frequency spectrum (right) a) “ruminating” behaviour b) “Eating” behaviour (65).



**Figure 3.** Example showing an increase in activity accompanied by a decrease in rumination during oestrus” (65).

It is necessary to understand the underlying mechanism of rumination tools for reliable PLF technology. For example, during eating, the cow must tear/pick up (eg grass) from the ground, chew it partly, and then swallow for rumination. As a result, the muscular movements observed in the neck are quite large and can be observed with the frequency differences of these acceleration measurements (5). This behavior is described using just a simple measurement of the acceleration at its height. With the difference between these two frequencies, the accelerometer processed map of rumination behavior is obtained (Figure 2a).

While the cow eating, the jaw movements of the cow indicates much more about rumination. Because in the course of eating, jaw indicates a wider movement pattern than the head. The frequency of behavior showing less rhythmic activity than rumination during eating can be seen in Figure 2b. The high level of variance produced during eating with lower frequency movements but lacks identifiable frequency peaks compared to the ruminant map (Figure 2b).

Figure 2 shows the regularly updated activity change of a cow during ninety minutes. When “estrus” behavior occurs in cows, “anxiety” levels increase, thus, this diversity can be observed in the behavioral model. The red line shown in the figure is considered a measure of how much the cow differs from its normal behavior and sends a warning message to the breeder for insemination. The other two lines strengthen the estimation for the insemination time. The green line shows the level of rumination decrease of the cow compared to the previous week (5). It provides an additional criterion to reinforce the diagnosis as it is known that rumination should decrease as estrus signs become evident in the cow. It also shows that the duration of feed intake during this period increased as a “dark blue” trace, compared to the average feeding time of the last week. This is actually the failure of the classification process to distinguish certain types of behavior. In fact, the cows do not eat more, they just spend more time rubbing other cows with their heads before the heat. Meanwhile, the difference observed is the map of secondary estrus behavior pattern (5) (Figure 3).

In addition to using eating patterns, there are 3D automated camera systems that can automatically measure the body condition score which is highly essential for maintaining the longevity, productivity, thus the animal welfare (67). Another interesting approach is monitoring the water volume, drinking frequency and the total water intake. These predictions are being used to detect the heat stress and the reducing the morbidity rates in dairy cattle (26), and growing rates in beef cattle (3).

With the help of smart animal feeding systems, feed consumption can be measured individually and at the same time, it can be ensured that the right ration needed by each individual is taken regularly. Apart from that, the regular weight gain and development of the animal is enabled to be more efficient with the use of these smart feeding models. While this increases the economic efficiency of the enterprise, it also helps to significantly reduce the workforce and early diagnosis of the health condition (stress, metabolic disease, etc.) and reduce the use of antibiotics for treatment (63).

**Monitoring systems of behavior and/or biological parameters:** The development of behavioral monitoring enabled the operational management interventions in large-scale dairy farms with a collar (transponder) or accelerometer that collects individual activity data from animals. Remote or wearable sensors can be uniquely combined with smart algorithms to continuously monitor a broad range of animal responses intimately linked to stress, health status, and welfare. The concept behind this technology is to create an accurate measurement that ensures reliable basic operational decisions for heat/respiratory stress (69), health condition like sick/healthy (63) and, welfare status social/conformations (167, 176). In order to gather health data for specific expectations (such as calving, mastitis, estrus, diseases) several methods are be combined or used alone including; body temperature (83) (vaginal, udder, ear, rectal and reticulo-rumen), indoor positioning for daily routine (milking and feeding), surveillance cameras, metabolic status (lameness, rumen temperature and pH boluses, rumen bolus, pH), external sensors (neck collar or ankle ribbon). We are able to read the estrus indicators of a cow through monitoring the position inside the barn, rumination behavior, stand-up time, lying time and inactive time with smart herd tracking systems. Based on these parameters, we can predict that the time of delivery with the abrupt cessation of rumination and eating behavior before calving (Table-1).

**Table 1.** Daily time budget of a dairy cow.

Lying/resting	12-14 hours
Ruminating	7-10 hours
Eating	3-5 hours 9-14 meals a day
Social interactions	2-3 hours
Milking	2-3 hours
Drinking	0,5 hours

Mastitis, as the main treat in dairy cows, is the focus for the development of various types of sensors in dairy industry as early warning and management systems would provide vast economic profits. Within the development of this sensor technology in nineties, various types of sensors are developed in advanced laboratories and introduced to markets. Nevertheless, routine detection of abnormal milk using visual observations during milking and availability of cow site tests limited application of these sensors in a large scale (72). It was the introduction of automatic (robotic) milking systems that boosted the need for sensors to detect clinical mastitis and abnormal milk due to the reduction in inspection time needed to identify mastitic cows. A variety of milk monitoring or sensing equipment to detect electrical conductivity, somatic cell count, milk colour, lactate dehydrogenase activity, milk yield, milk flow rate, incomplete milking have been incorporated and algorithms that use and integrate data captured during the milking process have been developed (79, 117).

Inline sensors are capable of monitoring and recording changes continuously as milk flows through the line or in automatically-collected milk samples. Inline sensors are adapted to be incorporated in conventional and automatic milking systems for mastitis detection (77). Inline sensors allow monitoring of subtle changes in milk non-invasively with remote accessibility to data for multiple diseases, and the ability to store the data. Unfortunately, a high number of false alerts makes individual changes in a single milk-associated parameter inconclusive for mastitis indication. Inadequate sensitivity and specificity by single-sensor methods is largely explained by the influence of other factors, such as milk temperature, milking interval, milk composition variations during the milking process (146).

Mastitis is associated with multiple changes in milk and udder of cow's udder and combining data from different sensors is helpful to obtain a much clearer picture and greater predictive ability. Hence, utilising multi-sensor information is the most recent approach to improve mastitis detection performance (92). Many multiple sensor-based approaches (6, 74, 85, 162) have been suggested to improve mastitis detection performance. In addition to mastitis detection, sensor systems progress toward identification of causative organisms, improvement of treatment and other management decisions at quarter, cow and herd level (128). The disease is multifactorial that affects both animal's physiological and behavioural responses. As sensors such as collarmounted accelerometers and heat detectors are becoming readily available to monitor behavioural changes automatically, such data might be of use for further enhancement of automatic detection of mastitis. Behavioural changes associated with mastitis include alteration in feeding time, lying time, standing time, self-grooming, rumination, head turning frequency, kicking, isolation character, preference for lying on one side, and increase of restless behaviour (39, 55, 89, 112, 135). Such sensor-derived data can increase the accuracy of mastitis detection if combined with milking related data (91).

Precise detection of estrus in cows is essential to maintain reproductive performance, especially in dairy herds using AI. Standing to be mounted is the primary and most characteristic external sign for determining when a cow is in estrus and considered sexually receptive for artificial insemination (137). Signs of estrus are often more intense in evening and night hours. Traditionally, estrus in cows is detected by visual observation (46). However, estrus detection by visual observation is highly labor intensive. In addition, increasing farm sizes and workloads limit the time available for observation of individual animals, resulting in unobserved estrus and remarkable economic losses (37). Furthermore, intensive genetic selection for high milk production has resulted in decreasing durations and weaker signs of estrus (140).

Precision monitoring technologies that continuously monitor and measure behavioral and physiological changes in the cow are commonly used to supplement or replace visual estrus detection. The development of automated estrus detection systems began in the 1980s and several types of automated heat detection devices for dairy cattle were marketed over the years (118). At present, a great number of fully automated technologies including pressure sensing systems that monitor mounting activity, activity meters, temperature measurements, video cameras, impedance or conductivity measurements, and hormone analyses are available (147). Parameters with potential to be used in automated estrus detection systems include but not limited to mounting events, activity level, lying time, rumination events, blood or milk progesterone levels, feeding time, body temperature (47, 59, 147, 156).

In general, automated estrus detection technologies detect estrus in cows mainly through secondary signs of estrus behaviour (59); mainly through multi behaviour patterns (82, 137, 152). To date, most technologies for identifying cows in estrus are based on automated activity measurement (47, 109). Pedometers or accelerometers attached to the leg or neck are able to detect estrus, with a predictable association with the timing of ovulation (9, 71, 119, 139). Automated activity monitoring systems are profitable for most dairy farms and producer satisfaction with their performance is generally high (146). Investment in automated activity monitoring technologies contributes to farm profitability in many scenarios (2, 114). Automated activity monitors use software specific algorithms to compare the activity of each animal with that of an individual specific previous reference period or with the average activity of the herd aggregated over time to create an estrus alert when a set threshold is exceeded. However, many environmental and metabolic effects as the type of housing, the herd management practices, animal health problems and heat stress have negative effects on the performance of automated activity monitoring to identify cows in estrus (2, 130, 148, 156). Other systems including video-software, body temperature measurements and biosensors integrated with in-line milking systems are expected to be combined with existing tools for multivariate estrous detection in near future (37, 118, 148).

Prediction of parturition is central to good calving management affecting animal health, animal welfare and farm economics (113). Supervision during the calving period enabling timely calving assistance is likely to reduce the risk of dystocia associated with increased calf mortality and morbidity, increased health problems in the dams, and the economic impacts that arise from increased treatment costs, reduced calf performance, and reduced reproductive efficiency (155). Historically, a combination of breeding records and visual symptoms has been used to estimate calving time; however, these efforts are hampered by the need for 7/24 monitoring and inconsistency between cows in visual behavioral and physiological changes related to calving (18).

Interpretation of behavioral and physiological changes related to calving, provide the opportunity to develop an automated system for the prediction of parturition, while no large-scale systematic research has provided insight into possible practically implementable solutions (147). Maternal body-temperature monitoring has been the first line application of precision technologies in calving detection, however, reticulorumen, skin, rectal and vaginal temperature monitors are not validated for prediction of parturition (23, 36). Recently, potential use of a calving prediction model based on continuous measurement of ventral tail base skin temperature with supervised machine learning (70) along with intravaginally inserted temperature and telemetry was reported (125, 163). Calving is related to many behavioral changes including lying bout, number of step and eating; while these parameters can be easily monitored using available tools mentioned earlier (124, 144). Meanwhile, it is still contradictory to attribute the changes in the mentioned behaviors to calving only for accurate prediction; as animals might exert other behavioral changes in noncommercial environment (151). Tail raising is another calving related behaviour. Tail-raising events dramatically change prior to calving (81, 115). In a recent study, a tail-mounted inclinometer sensor was used at 5 different intervals (i.e., 1, 2, 4, 12, and 24 h until calving) to calculate sensitivity and specificity. Depending on the interval preceding the onset of parturition, sensitivity varied from 19 to 75% and specificity from 63 to 96%. (178). As a distinct predictor, tail raising monitoring is considered as the best behavioral change to estimate the time for calving using this smart systems; while this prediction accuracy can be increased by combination of eating and rumination behaviors (116).

These systems continuously records individual animal and measured data are processed with sophisticated software, and the data is downloaded wirelessly to a computer each time the animal enters the receiving area of a base station. Alerts showing the animal's status are displayed on a local computer or in the cloud. Each leash learns normal behavioral patterns and the owner warns only when intervention is necessary and allows the farmer to plan a corrective action. Significant differences in the variance of the measured raw data allow the derivation of various behaviors such as rumination and feeding (51, 153). The energy consumed by the animal during its daily routine is individually mapped and defined.

The most important reason for the immediate adoption of animal tracking technologies has been the need to optimize offspring yield in dairy cattle. In cattle, it caused an increase in fertility, selective breeding practices, other welfare factors such as reproductive diseases (eg metritis, ovarian cyst, foot diseases), and consequently a decrease in fertility (58). Additionally, lack of management practices, malnutrition, and inadequate estrus detection contribute significantly to low pregnancy rates. The cost of bovine infertility arises from the loss of income from milk production, artificial insemination, labor cost, and late calving (58). This situation causes an estimated loss of approximately \$ 2,333 per cow (98) and according to de Viries (2007), it is \$ 555. Although the

fertility of the herd depends on many factors, estrus detection is predicted as the most important factor. Detection of estrus in cattle was carried out by a skilled observer or farmer looking for visual signs of estrus.

### The Economical Aspects of PLF

In principle, the tools related to precision farming serve a purpose in the management of input allocation to the farmers to decrease the expense of production and increase the outputs by aiming to improve health status, management and production efficiency as well as reducing the labor (14, 146). However, these technologies are available at a considerable price (Table 2).

**Table 2.** Price range of various precision livestock tools.

Item	Location	Targeted Measurement	Price	Notes
<b>Identification</b>				
<b>Ear tag (RFID)</b>	Ear	Identification/ accelerometer (X, Y, Z axis), Body temperature	1-5 € \$1,425.00 for reader	Standard price with little variations
<b>Collar-Transponder</b>	Neck	Identification/ accelerometer (X, Y, Z axis),		Varies according to size and manufacturer
<b>Ruminal bolus</b>	Rumen	Identification Rumen pH, core body temperature	5–450€	Varies according to size and manufacturer
<b>EID Injectable</b>	Subcutaneous	Identification, body temperature	5 €	Only available for dogs with temperature measurement
<b>Injectable EID reader</b>	Subcutaneous	Laboratory Animals	150-500 €	Varies according to manufacturer
<b>Wearable sensors</b>				
<b>Accelerometer</b>	Ear, leg	Activity tracker	\$55	
<b>GPS systems</b>	Neck, leg	Geo-satellite positioning system		
<b>Precise Farm Management Tools</b>				
<b>Cow Scale</b>	Stationary	Weight	5 500–7 280 €	Price difference based on size and complexity
<b>Feeding computer (Spider)</b>	Stationary	Automatised feeding	€ 225.75 per unit	Controls up to sixteen feed dispensers within a ten-metre range.
<b>PipeFeeder</b>	Stationary	In-parlour feeding	950-440 €	Prices are per milking point and based on a 2x8 milking parlour. Mounting hardware included.
<b>Feed Station walk-through</b>	Stationary	Walkthrough forwards	4000-6000 €	One/two type of feed
<b>Walk over weight</b>	Stationary	Weight	12 000–15 000 €	Product available for cattle
<b>Automatic Dispensing Liquids</b>	Connected to feed station, milking robot or milking parlour	Liquid intake	Float set (€ 48.08 per unit) not included / 500-2100	Mounting hardware included.
<b>Pasture management tools</b>				
<b>Virtual fencing</b>	Neck, nose	Sound and electrical vibration	\$5000 to set up \$60-90 each collar	Ongoing maintenance



**Milking parlour technology**

<b>Smart milking parlour</b>	Stationary		\$40 000–80 000	Variable price according to outfitting, 12–24 stations
<b>Robotic milker</b>	Dynamic/rotational		\$150,000-200,000	for 50 to 70 head of cattle
<b>Software</b>				
<b>DairyLive</b>	On PC		\$179.00	Dairy management for up to 50 animals
<b>Automated health-monitoring system</b>	On PC		\$150-\$175 USD per animal (collars + data system)	
<b>CowView</b>	On PC/Smart Phone	Standing time, frequency and time spent in cubicles, time walking, how far and how fast, frequency of visits and time spent at the feed table.	£150	
<b>Let's nurture</b>	On PC	Male and Female Wire Gps device Acid sensor Lithium battery Heart beat sensor	\$8000-9000	
<b>Let's nurture</b>	On PC	QR scanning to connect with device Alert for treatment Show all Cattle list Medicine dates Animal Doctor list Hospital list Gps tracking Report of whole day	Cost for application development \$7,500 – 10,000 (Include in android and IOS application) and \$5000 for web application.	
<b>Smart phones for cows</b>				
<b>Collar</b>	Smart Phone, Virtual Glass	Temperature calving time Estrus detection	The GSM radio costs £2,500 collar £70-£80.	

**Table 3.** The risk of false positive for health disorders.

<b>Alert</b>	<b>Maximizing Sp</b>	<b>Maximizing Se</b>
	<b>Rumination or activity</b>	<b>Rumination or activity</b>
Sp (%)	97	51
Se (%) (n=404)	21	77
False Positive Rate (Detection/d/100 cows)	2	19

The economic value of the PLF naturally depends on various key factors, including the herd size, characteristics of the farm, accuracy of the reliable data, the value of obtained information that could prevent expenses, number of workers, as well as the social impact. Livestock farms have remarkably variety in terms of their size, housing, nutritional practices, labor, genetics, keeping the records, reproductive management, herd health and welfare, overall substitution strategies, and personal goals, so when there are PLF systems, the concept of "one size fits all" are not valid for all. Even if the critical action could be the

same, the ROI (Return on Investment) may vary based on the application used to enforce the action (27, 142). The farm based examples have been illustrated and assessed in a limited number of studies although in general, the returns to investment are still not clear and in terms of yield and economic performance, the output of these precise technologies have not been well-demonstrated yet (7, 90).

In an example, one of the most commonly preferred systems, the implementation of an automated heat detection into a labor and capital intensive dairy farm provided an estimated of € + 7,362 profit while the

economic benefit reaches up to € 3,815 in a labor intensive capital extensive dairy farms (86).

Apart from that, welfare monitoring of the animals is frequently related with production and profit. For example, owing to the use of PLF technologies metabolic disorders such as subclinical ketosis can be prevented. A quick detection of subclinical signs of ketosis could be achieved with an in-line milk test for ketone bodies (160), that could prevent the further economic lost due to decreased milk yield and veterinary treatment cost as € 709 per animal for clinical ketosis. Moreover, if the welfare is emphasised in the decision model, significant value will remain gained via targeted treatment due to the information provided by these technologies as observed in Subacute ruminal acidosis (141, 142).

Even though few studies demonstrated the negative effects of automated milking systems on economic performance, currently it is presumably the most widespread PLF technology implemented worldwide due to the reduction in extensive labor and maximizing the time efficiency (73, 146, 161). Similarly, a great economic difference could be encountered between the farms which inseminate once owing to the knowledge of estrus timing provided by PLF technologies and inseminate two-three times a day (99).

The accuracy of predicted ROI depends on the level of monitoring. For example, pig groups ready-slaughter or significant disruption in pig growth can be determined efficiently with multi-level monitoring body weight (164, 165), although, since there are no individual warnings, it is impracticable for a farmer to identify and treat a specific pig. The economic benefit of early treatment of a pig will affect the value of individual identification. Similarly, a dynamic monitoring system was developed for litter size at the herd to estimate future production (17). This idea was adapted to automated milking system data in dairy herds as changing the feeding strategies for selected cows by the overall response measured in milk production (164). In this sense, PLF technologies can provide different and useful decisions for farmers, but elaborates the determination of ROI since more information could be profitable for particular types of farms (141, 174).

The intermittent use of PLF system aids to the detection of the problems a few hours early that could provide the time to act on critical decisions in particular situations to prevent further economic loss such as tail biting on a pen (172).

The low or even negative profitability of some PLF tools (16, 61, 141, 174) may not initially rationalize the large investments of purchasing these systems. However, the use of the framework to assess economic ROI also reveals that most cases of how to use supplementary information are related to operational decisions since the more precise information can provide strategically superior decisions as well as long-term implications. The effects of modifying strategic decisions can also be tangible, making it difficult to define (86, 96, 161) while making them visible will increase the transparency in critical evaluation of the ROI.

As a summary, economic investments (costs) arising from the purchase of sensors and vehicles, would compensate the profits from avoided production problems, along with associated with avoided/reduced losses.

### Concerns related to PLF systems

**Accuracy of the tools:** Although the PLF-tools provide objective measurements, several factors can affect the sensitivity and specificity of the collected data/information and its interpretation. For example, in a broiler farm, the average weight of the flock is assessed by manual measurements or automatically by random sampling a certain number of birds to reveal the growth trend of the flock. Nowadays, “step-on scales” are developed to automatically collect the average weight of the birds in the flock. However, factors determinant of the accuracy of automated weighing relies on the ability of the birds to visit the scale, and in such conditions that impair the mobility of the birds as aging, having excess weight, sickness and lameness, the system may fail to represent the growth trend of the whole flock. In order to encounter these limitations, various methods have been introduced. The bodyweight of broilers on average with a relative error of about 11% from image surface area by introducing a computer-assisted image analysis was estimated (42). Since PLF systems are being improved and updated continuously, more reliable technologies replace the old ones as in this situation, due to the discovery of a relationship between weight and vocalization frequency, it was proven that a reasonably accurate growth trend could be obtained at the farm level (56). In another research, an automated method has been implemented to report the malfunctioning in a broiler farm by using cameras and image analysis software and resulted in a 95.24% accuracy of events (20 out of 21) in real-time. The PLF system used an algorithm that compared the measured distribution of animals with a predicted value to give an alarm to farmers when a 25% more difference was found in the measured distribution from the predicted value (87). When compared with a different algorithm utilizing water use of the birds (132), true positive cases were found 33.3% more while false positives were reduced from 28.6% to 0% with the distribution modeling. Another camera-based technology equipped with automated image processing and transfer function modeling has been utilized to estimate the water use of pigs and resulted in 92% accuracy in the estimation of half-hourly water use (52).

Based on the findings of (71) and (84) the sensitivity of the activity meter to detect the cows which were about the ovulate was 80% while the specificity was 95%.

In a recent attempt to validate the tracking ability of a PLF system, two rounds of video recording were analyzed and resulted in an overall accuracy of over 90% due to the performed optimizations in system configuration after the first recording. Further research has been conducted to determine the variation of the measured values in different tools. Although the lying duration of the dairy cows was significantly correlated between two systems ( $r=0.94$ ;  $P<0.001$ ) the correlation for the number

of steps was found lower ( $r=0.74$ ;  $P<0.001$ ) presumably due to the difference in the measuring steps between the two systems (53). In addition, a study on the detection of different health disorders with cumulative summary of rumination and activity data, 40% of the health disorders detected by farm staff with the sensitivity around 28% for mild lameness to 85% for severe mastitis. Roundly, half of the health disorders were detected one day earlier than the farm personnel.

**User Friendly Interfaces:** The use of information systems does not always lead to increased business efficiency. As the information environment becomes increasingly saturated, users may start finding the data search process confusing (40). In addition, the order of information within a system can be complex, overmuch data appears on the screen, leading to information overload for the user (184) When information overload occurs, the users' decision-making performance decreases (34).

In addition, systems currently used without considering user friendliness (111) but expected to improve decision-making performance (169). A well-designed user interface can positively affect the decision-making performance of users (182). A study was conducted to overcome this issue and developed a decision-making performance and cognitive load for potential users interested in livestock, animal biotechnology and veterinary science and farming.

The importance of friendly user interfaces increase due to the integration of these technologies into the daily life routine (25). However, when the different potential users have considered the user interface becoming a key element for the system (31, 68). Nowadays systems are can be classified into basic 3 categories as software, computer, other devices that operate codes and utilize a visual graphics can be viewed remotely. Thus, technology can communicate with human beings through graphical elements, messages and early warning alerts. Furthermore, the system could learn the system elements with machine learning in time and carry on working without the need for human touch (52) and information can be understood differently by users depending on their cognitive styles (117).

Information and communication technologies revolutionized the traditional farming system and became popular these days. The most triggering factors are the educational level between farmers and difficulty to implement new technologies (29), limited information and communication infrastructure in rural areas (157) low interest of understanding and use (186).

Another issue is the human factor which needs to be improved by designing the friendly user interfaces (168). Most of the previous work on agricultural information systems focused on system elements other than interfaces to improve system utilization. However, poor user interfaces are frequently cited as a problem in agricultural information systems (44, 110).

The user interface serves as a complex programming language and a communication tool between users thus the interface is a key essential. Therefore improving the

interface design makes it easier to understand the log of farm data and make correct decisions (158). There are several examples of the commercialization of PLF techniques in livestock production. The models that are being used for commercial adaptations are; the use of robotics, egg counting, bird weighing, environmental control, precise feeding systems, climate control, automatic disease detection, and growth measurement (64). Overall, there was limited evidence of commercial PLF products used on farms. As expected, farmers in techno-friendly countries are more likely to embrace technology to reduce their dependence on hard-to-find (and expensive) workers and to make their lives a little more comfortable (87).

PLF technologies are mostly developed by researchers from the beginning and that have received support from the private sector only in the last decade. This researcher-private sector collaboration is a critically essential step in the development of friendly user interfaces for the use of the ministry officials and breeders (88). Artificial intelligence systems provide suggestions by the breeder about which animal is sick, which is in heat, and which will be deliver. That's why, many PLF systems set normal range of parameters for the infrastructure of the enterprise and the routine behavior of the animal and alert the breeder when any deviation from the normal range take place. This provides the basis of reliable information and correct decision-making in the routine learning process of artificial intelligence that requires mastery (134).

**Security Issues:** Precision livestock technologies are gaining more attention due to the future possibility to comply with consumer demands and the global food supply chain. There are numerous precision farming use cases (12, 32, 38, 105) that indicate the impact of this new farming practice paradigm globally. In India, farm data have been used to predict and prevent crop diseases that reduce the risk associated with crop production failure (171). Smart agriculture employs not only at the production stage where health related issues are on great focus, but also the entire food supply chain. This enables a whole new revolutionary model, where big data from the entire agriculture business structure is processed to provide critical insight for on-time operational decision making (5). Intelligent agriculture increases traditional agriculture practices by offering precision tools in the field. That tools and sensors work synergistically to deliver improved crop yields as well as productive farming experiences. In spite of the fact that advantageous for industry efficiency, the utilize of diverse, IOT tools has uncovered potential cyberattacks and vulnerabilities within the agriculture industry. These assaults offer the capacity to remotely oversee and utilize sensors and independent vehicles (drones, smart tools and etc.) within the field. Potential agricultural attacks can provide a risky and inefficient farming environment. Different examples of a cyberattack have been generated, and some of these examples are overwhelming. Such gigantic facilitated assaults moreover alluded to as agro-terrorism (94), in expansion, illustrate the potential of disturbing the

economy of an agriculture-dependent country. There are such reports on the potential risk of cyber-attack scenarios in smart farming practices and highlights the critical control points for researchers (122). A sophisticated farm-terrorism could impair the millions of consumers' health globally. Along with that fact, such a threat on farming systems can decrease the reliability of consumers' preferences and may impair the trustworthiness of the exporter countries. In a report published by the United States, it was emphasized that cybersecurity is extremely important in the agriculture and livestock sector and is one of the critical control points for national security. While 11 cyber-attacks were reported in 2016, he emphasized that the threat of cyber-attacks targeting the IoT infrastructures used by farm systems may increase. Compared to other sectors (banking, finance defense industry, etc.), the awareness about agriculture and animal industry is still weak." This offers an enormous gap between using smart farm technology and ensuring it is accurate and permanent. If not constantly monitored, cyber-attacks against smart farming technologies can have profound effects on various stakeholders in the ecosystem. These groups include farmers, end consumers, food processing industries, agricultural cooperatives, animal husbandry, government agencies, and countries that are critically dependent on agriculture (104).

Confidentiality of the data collected via PLF tools has great importance both for farmers and technology companies. Due to misuse or loss of the data, farmers may face financial or emotional impacts whereas companies may face a reputational loss. Possible scenarios might include the leakage or theft of the data, use of confidential information either to gain profit or to damage a company and/or foreign access to unmanned aerial systems. Similarly, the integrity of the data could be compromised by tampering with the data to interfere with the livestock sector, introducing rogue data into the network of a sensor to damage a herd as well as the inadequately vetted machine learning. Apart from that, specific threats to equipment availability may have an origin of either natural disasters or cyber-related issues such as disruptions to space or ground-based positioning navigation and timing systems as well as to the communication networks (127).

**Animal-Farmer Relationships:** The daily activity of the farmer is started to change by the adaptation with smart farming technologies directly or indirectly by the need for less contact comparing to the traditional farming managements. This new adaptation to the PLF concept may lead to the extent of the distance between human-animal relationships (57).

Meanwhile, precision livestock farming can damage an animal-farmer relationship. The time that a farmer employs to spend with the animals will decrease in time. The habit that farmers will gain through the automatized system might reduce the beneficial opportunities and recognition abilities in between. In the traditional animal farming system, there are many common practices that require direct human-animal interactions like; dehorning, injections, milking, treatments, etc. The less time that farmers spend with modern technologies, the more animal

will become tempered. The ratio of positive and negative interactions can be altered equally. Regular opportunities for beneficial interaction, such as feeding times, may decrease with the bonds they create (175).

Again, the beneficial effect of PLF on the farmers daily routine could be denoted such as the decrease at the workloads like moving the animals to the dispenser pen or the milking push. Current milking technology under the smart robot control made it possible to milk the animal when they need or that are cow are not self-milking. Another advantageous condition is that when an animal received a stressful practice the rumination behavior is altered so consequently the production capacity and welfare. This condition might turn into something that, farmers never to have to spend time to bond with the animal (76, 95).

The complicated task needs to require some technical knowledge for farmers to sort the big data, visualize the data as graphics and finally take a decision with the right judgment. This might create another risk about the losing computational skills by the owner. On the other hand, the PLF provides the understanding of individual animal identity and can totally change the perspective of point in animal husbandry (17).

The adaptation of animals to new systems are relatively quick compared to humans. A study showed that the robotics milking system gives more freedom to the animal and interestingly when it is given free of choice as well (49), given that the animal has to do first, it is still a restricted system on which movement circuits are imposed. If he wants to rest or feed, go over the robot. The PLF technologies not only providing freedom to the animal but also created more time to spend by the farmer and take the focus on animal welfare and positive interactive habits (175).

The most recent technology may decrease the distance between humans and animals by collecting more reliable data with PLF, thus more individual information at the herd level. Nevertheless, the real scenario behind this is hidden underneath that "numbers farming" with providing more-in-depth information about their needs. There are opposing views about the discussion on factory based agriculture system. Some animal rights advocates claim that the technology actually triggers the growth of a factory-based agricultural industry. This claim must take into account seriously and the truth behind it must be understood and use as an encouragement for better animal care and welfare. This gives farmers the power to make better choices based not on profit alone, but rather on the actual needs of the animals and their care at all times. Another important point is the intensification of animal production systems with PLF technologies. There is a risk of abuse the animal via production climax thus altering animal welfare. Apart from that, the reliance to these technologies may lead to a point where it is possible for the owner to fail to notice the signs of important diseases due to the decreased time of animal-farmer contact (76).

In addition, new developments in the animal behavior field and updated biological parameters could change how farmers perceive animals and how animals

perceive humans. On the other hand, with the help of artificial intelligence and computers, it can affect the development of decision-making mechanisms and new job descriptions, how the new generation farmers experience today's profession and dreams, and their job satisfaction or dissatisfaction. Finally, existing technologies may not always create a significant distance between livestock and farmers. Technologies today may perhaps enable the development of new relationships with the animals of millennials. (75).

A study conducted on the human-animal relationship as a survey; where farmers were asked what they believe about the human-animal relationship. Most of them tried to avoid the question for two reasons. The first is the definition of the new term and the other reason was the personal emotional distance. For this reason, four farmers thought it was unrelated to their profession. It was more straightforward for farmers to discuss their views on an exact human-animal relationship. Frequently they spoke of the welfare of the animal, and some spoke of the animal's lack of fear of humans, even of a mutual trust between the farmer and the animals. For some farmers, good production levels reflected a satisfying human-animal relationship. For the majority, a good human-animal relationship makes it easier to work with animals, regardless of the breed. They also talk about the well-being of the farmers and good livestock farming with equipment. Interestingly, a certain number of farmers that they surveyed are reported in some studies claiming the human-animal relationship going worse (94). On the other hand, we all agree that PLF technologies must be reinforced to build up a better relationship with the animals and humans not to worsen them, but to improve and transfer to the next generations.

**The ownership of the data:** There is an increasing debate on the ethical issues related to precision livestock farming. One controversial discussion is related to the collection of data from animals, as if they are an instrument to improve business process control. While, animal welfare improvement relies on accurate data and real-time knowledge to be collected from these devices, strict considerations to minimize the stress for capturing and handling to fit the collar or any tracking device should be considered; as no animal "likes" to be tagged. This should be in accordance with animal rights, as animals are sentient beings that have moral status and preference autonomy that they have vital interests humans must not override" (1).

Another issue is related to the possibility of mechanization of the breeding systems as it is expected to disturb human-animal relationships, turning animals to objects of data. Objectification perspectives within "treating animals as objects" and "turning animals into as objects" and instrumentalization perspective on the frame of PLC, requires novel intuitions of the ethics of care (19).

As the PLF systems become more widespread tools in livestock industries, a considerable amount of data is being collected in the meantime, arising discussions on data distribution and ownership (28, 143). Apart from a

number of exceptions, the data produced is not yet distributed fully among the food chain actors and there is a lack of compatibility between data sets that may favor the quality assurance of the supply chains (103). It is still in a debate who has the potential ownership of the collected data, between the two parties, the farmer, as the owner of the animals and the software manufacturer as the data processors.

Rapid improvements on the current PLF technologies rely mostly on continuous monitoring of the animals as well as deducing the relevant information by analyzing the raw data. In fact, the information as actionable insights transferred from the monitoring, in the form of charts and reports are more valuable to the farmer than the raw data. However, the companies that develop PLF technologies can benefit from this data, more particularly when it is combined with the data from other companies to form big data. Furthermore, companies can produce income directly by selling it as reference data. Besides, a great potential of value lays in for other stakeholders as third parties in the circulation, such as veterinarians, feed, breeding pharma and technology companies, slaughterhouses, retailers, the consumer, processors, certifiers, citizens, governments and researchers (93). Therefore, it might not be fair for the farmers to be the only one that pays for the technology while other stakeholders depend on the data generated by the farmer to both to and contribute to the PLF platform. The determination of the data ownership must be properly regulated with legal frameworks in order to establish collaborations and to build a future market for agricultural data (21).

### **Ethical questions related to the IoT**

- IoT used for medical purposes on animals would have the status of medical devices if used in humans. For humans, medical devices have specific regulations to ensure the health and safety of the user. As surprising as it may seem, there is no regulatory framework in France concerning connected objects in terms of both expected efficacy and safety. The implementation of a harmonized methodology for evaluating these tools and a material vigilance system would undoubtedly be necessary.

- These tools that continuously produce data (and sometimes alerts in case of deviation of observed data from expected data) can be stressful for their users, especially when the tools lack specificity (alerts generated on non-diseased animals). Faced with this incessant flow of data and alerts, the risk is that the owner loses confidence in the tool (and stops looking at the data at the risk of missing sick animals) or, on the contrary, that he decides to do something at the first alert without discernment. The owner's better knowledge of the animals via these IoT and the optimization of the care provided thus relies largely on the performance of the tools and their operating conditions.

- The absence of a specific regulatory framework for IoT on animals often means that the only choice to equip the animal is often made by the owner. While it is obvious

that there can be no question of obtaining the direct consent of the animal, it is legitimate to question the circumstances in which one can freely decide whether or not to equip it and whether one can simply freely decide without control to equip animals, particularly when the objects may be invasive (number of tools, nature of the tools). The question of an opinion, in the absence of validation, by a specialist in animal health or behavior arises in particular to validate the interest of the equipment and, if necessary, the choice of technical solution. It is also essential that users be properly trained in all the potentialities of the tool.

- Finally, connected objects require the use of natural resources (metal, electronic circuits and rare materials that are sometimes difficult to recycle) and also energy for their proper functioning and the storage of associated data. Some connected objects can offset these environmental impacts if they make a greater positive contribution, for example by reducing the quantities of inputs or water consumption in crops. In any case, their overall impact (interest for the animal, the farmer and the environment) should be considered.

- The issue of the digital divide and white zones can also lead to a lack of equity between farmers and between zones.

### **Ethical questions related to the impact of connected objects on the human-animal relationship**

- The diversity of the available IoTs makes it possible to access very fine data at the animal level that can modify or influence the perception that the breeder or owner has of his animal. Thus a farmer can now go beyond the knowledge of his animals by their simple performance (as allowed by the first tools developed) and have access to their movement, their behavior (feeding, sleeping) and their location. This can allow a better understanding of the animal and allows a more personalized approach to be envisaged.

- Nevertheless, while this use of technology can provide real working comfort in a context of a constantly decreasing workforce and increasingly large herds, there is a risk of a form of distancing between the farmer and his animals. As an example, a study carried out among cattle breeders with heat detection devices underlined the positive impact perceived in terms of working comfort (including safety at work due to less handling) but highlighted a fear of the farmer of loss of animal competence. It is important to consider these tools not as substitutes for the farmer's eye, but as a complement;

- The massive and continuous collection of data of interest (milk production, growth rate, behaviors, disease resistance for example) opens the way to what is known as high-throughput phenotyping, i.e. the characterization of all the apparent characteristics of an individual, continuously and almost in real time using connected sensors and tools. This fine phenotyping is the key to then carry out genomic studies allowing the selection of

animals carrying the characteristics deemed to be of interest (such as disease resistance, a phenotype that is very difficult to characterize classically). To do this, the construction of the tools is fundamental in order to associate different people from different backgrounds from the outset to develop the tools, while not forgetting to associate the end user in particular. Connected tools could make it possible to bring out the individual in the group and thus give visibility for the breeder to isolated individuals, especially in large numbers. However, one could fear the opposite effect, i.e. an extreme standardization/standardization of the animals leading to genetic impoverishment or loss of the individual by eliminating individuals that go beyond the hoped or expected standards.

### **Ethical questions related to the status and use of data from connected objects**

- Potentially, the data collected through the different IoT can serve several purposes and several people. Also, a provider is transparent if all purposes are exposed to the user. In addition, as a data collector, it must demonstrate data governance that ensures that there is no data leakage to a third party. Similarly, the question of data valuation beyond the farm arises. Indeed, for example, the high throughput phenotyping type data allowed by these tools must be able to benefit the "breeder" without the breeder paying twice for it (by first equipping himself and then paying more for the data of interest that he has helped to produce).

- Continuous and possibly remote access by the veterinarian to the data generated by the IoT embedded in the animals opens up interesting perspectives in terms of teleconsultation or tele-expertise capable of optimizing the health and well-being of the animals, particularly in areas of medical deserts that are also used on a daily basis in non-deserted areas. However, the help that these IoT could bring cannot hide the need to address the issue of land use planning and permanent health monitoring.

- The mass of data generated may make it possible to rethink the client-veterinary relationship, opening up the field of telemonitoring and an "increased" clinical examination for the veterinarian, who would thus have access to measures not otherwise available or continuously, whereas they are currently only accessible to him at the animal's bedside. Conversely, the breeder should not be overwhelmed with information and contact the veterinarian as soon as the first data is received or contact him only in a dematerialized and frenetic way. It is indeed the complementarity of the approaches that should benefit the animal. The challenge is then to explain to customers what attitude to adopt when faced with these tools, which cannot entirely replace bedside care. The use of these new technologies will also require veterinarians and owners (breeders, pet owners) to be adequately trained in the use of these tools and the data and alerts they generate.

Thus, beyond the undeniable technical advances made possible by the connected tools, the fact remains that

they raise ethical questions that, if not resolved, deserve to be debated.

### Conclusion

The advance of novel technologies and informatics has increased the worldwide demand for integration of PLF systems to local farms. While monitoring tools for physiological, behavioral and environmental parameters and analyzing software are evolving around the Internet of Things; PLF provides cost-effective production with prudent/less drug use and is relatively more environmentally friendly. As IoT technologies for PLF are still in the development stage and information is more valuable in this era of the big data world, legislations and regulations, unfortunately, follow behind, in terms of safety and ownership of the data. Deanimalization and commodification are the main ethical issues discussed around the PLF topic. The increase of the efficiency and sustainability of farming and livestock production is inevitable by properly applied PLF; where the welfare of the animals would reflect the animal health. This would enable the traceability of the food chain and food safety.

### Conflict of Interest

The authors declared that there is no conflict of interest.

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