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Precision livestock farming in buffalo species: a sustainable approach for the future

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ABSTRACT

The increasing global demand for animal-derived foods in a climate-changing context requires innovative strategies to enhance farm efficiency and sustainability. Livestock farming is facing increasing pressure from consumers seeking high-quality products, improved animal welfare, and greater traceability. At the same time, the sector is resource-intensive, requiring significant inputs of land, water, and energy, while also contributing to environmental impacts, including greenhouse gas emissions. Precision Livestock Farming (PLF) represents a valuable strategy to tackle or mitigate these challenges by leveraging advanced sensors and digital communication tools for the continuous monitoring of animals and their surroundings. By collecting real-time data on production, reproduction, health, welfare, and environmental parameters, PLF supports more informed decisions and promotes a more sustainable and efficient livestock management system. In recent years, PLF technologies have been applied particularly to species such as pigs, poultry and dairy cattle. Notably, the transfer and adaptation of PLF technologies from dairy cattle to buffalo farming have contributed to the optimization of key farm processes in Europe, particularly in Italy, where the buffalo sector represents a growing market. These advancements not only highlight the potential of PLF in improving efficiency and animal welfare, but also may offer a valuable foundation for its adaptation in other contexts. In particular, dairy buffaloes is expanding in developing countries across Asia and Africa, where buffaloes play a central role in food security and rural economies. However, transferring PLF solutions to these regions requires careful consideration of existing limitations, including scarce financial resources, inadequate infrastructure, and insufficient training for farmers and technicians. This review examines recent advancements in the application of PLF to dairy buffalo farming, highlighting its impacts, current challenges, and future prospects for broader implementation.

1. Introduction

1.1. Livestock challenges and critical aspects

The world population currently stands at approximately 8 billion and is projected to reach 9.7 billion by 2050 [1]. This growth will be particularly pronounced in developing countries of Africa and Asia, where about 80 % of the world population will reside. Consequently, the global demand for both plant- and animal-derived products is expected to increase by 70 % compared to 2010 levels [2]. Annual cereal production will need to rise by approximately 3 billion tons, and annual meat production will require an increase of over 200 million tons to reach a total of 470 million tons by 2050 [3]. However, achieving these targets is constrained by the limited availability of additional arable land [4,5]. In addition, climate change may exacerbate these challenges, negatively affecting crop yields, livestock productivity, and overall food security [6,7].

Over the previous 50 years, the livestock sector has undergone

Abbreviations: PLF, precision livestock farming; GHG, greenhouse gas; AMS, automated milking systems; LCA, life cycle assessment; IRS, Infrared spectroscopy; SCC, somatic cell count; RFID, radio frequency identification technology; SNPs, single nucleotide polymorphisms; IRT, infrared thermography; SCS, somatic cell score; DSCC, differential somatic cell count; THI, temperature-humidity index; EC, electric conductivity; LMD, laser methane detector; NIR, near-infrared; MIR, mid-infrared.

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significant transformations aimed at improving production efficiency. However, modern livestock farming should balance the need for enhanced productivity with reduced environmental emissions, and higher animal welfare standards. Despite its critical role in the economy, nutrition, and public health, livestock production remains one of the most resource-intensive sectors [8]. For example, 26 % of ice-free surface is used for grazing, and one-third of global cropland is dedicated to livestock feed production [3,9]. Livestock farming demands significant water needs for crop and forage production, drinking, cleaning, and overall management [10,11]. Moreover, livestock production contributes substantially to greenhouse gas (**GHG**) emissions, accounting for about 30 % of agricultural emissions, which is responsible for 9.20 % of the total GHG emissions, and 4.92 % of global emissions [1]. Methane from enteric fermentation and nitrous oxide from waste management are the primary contributors to GHG emissions [12,13]. The concentration of animals in limited areas increases environmental pressure, particularly through nitrogen and phosphorus pollution of soil and water [14].

Although livestock production is often criticized for its environmental footprint, it also delivers multiple societal and ecological benefits. Animal-derived proteins possess higher biological value than plant-based alternatives, helping to prevent the risk of macro- and micronutrient deficiencies, particularly in vulnerable populations [15]. Moreover, ruminants can efficiently convert forages from marginal or non-arable lands into high-quality products, utilizing areas unsuitable for crop cultivation [16]. Livestock farming plays a crucial role in preserving landscapes, by preventing land abandonment and limiting the spread of invasive vegetation. Grazing maintains habitats and supports biodiversity, especially in regions where mechanized land management is unfeasible [16]. In marginal areas, livestock systems also support rural employment, helping to sustain local economies and counteracting the trend of population movement toward urban centers. This can contribute to a more balanced settlement structure, maintaining essential services and social cohesion. In addition, a geographically distributed agricultural sector enhances land use efficiency and national resilience by reducing reliance on a few production areas, thereby strengthening food security and lowering vulnerability to extreme weather events and market fluctuations [17].

1.2. Precision livestock farming (PLF): a transformative approach to sustainable livestock production

Precision livestock farming (PLF) represents a paradigm shift in animal husbandry, characterized by the continuous, automated, and real-time monitoring of physiological, behavioural, and productive parameters using advanced sensor technologies and information systems [18]. Through the systematic collection and integration of high-resolution data at both herd and individual levels, PLF enables data-driven decision-making which, in turn, may improve production efficiency, animal welfare, and environmental sustainability [19]. Traditionally, livestock systems considered animals as homogeneous groups due to practical constraints. In contrast, PLF technologies, such assensor-equipped automated milking systems (AMS), allow for individualized monitoring. This approach reconceptualizes the animal as a complex, dynamic, and time-variant biological system, requiring adaptive management strategies that reflect intra-herd variability [18,20]. As a result, PLF supports a shift from conventional group-level practices to precision, animal-centric management, enhancing both the responsiveness and effectiveness of livestock systems.

1.3. How PLF technologies may have an impact on sustainability and social aspects

Precision livestock farming technologies have the potential to significantly enhance sustainability by optimizing the balance between inputs and outputs. Life Cycle Assessment (LCA) is one of the most widely used tools for evaluating the sustainability of production systems, as it quantifies multiple environmental impact categories, including greenhouse gas (GHG) emissions, water and land use [21]. Conventional LCA methodologies often rely on generalized datasets able to capture an average condition instead of unique dynamics of individual farms. By incorporating continuous data collection, facilitated by PLF technologies, the accuracy and relevance of LCA in livestock systems may be significantly improved, resulting in more robust and actionable evaluations. Such data-driven insights also support better on-farm decision-making; for instance, the early detection of health issues can lower veterinary costs and reduce the use of antibiotics, thereby enhancing economic viability and potentially mitigating the risk of antimicrobial resistance and its associated social costs [22]. In parallel, specific PLF applications such as AMS contribute to labor efficiency by alleviating physical workload, increasing operational flexibility, and improving farmers' work-life balance [23].

1.4. Available PLF technologies

Precision livestock farming technologies employ various sensors, which can be broadly classified into three main categories [24–26]:

1. At-Cow sensors: these devices are directly attached to the animals and are essential for tracking individual health and behavioral parameters (Table 1). For instance, accelerometers, which vary in type and placement, are commonly placed on the hind leg, collar, or ear tag, and are used to monitor locomotion and rumination patterns, facilitating the early detection of lameness and digestive disorders [27–30]. Other devices, such as ruminal boluses can measure ruminal internal parameters such as pH and temperature, providing critical insights into the animal's metabolic state [31,32], while vaginal devices can track physiological changes related to reproduction [33,34].
2. Near-Cow sensors: positioned within the animal's immediate environment, are designed to monitor external factors that may influence health, welfare and productivity (Table 2). Among these, cameras and walk-over weighing systems, often integrated with artificial intelligence, allow for assessment of animal's body condition score. This reduces operator subjectivity and enables more accurate monitoring of nutritional status and precise growth tracking [35,36]. Detectors placed close to the animal offer the advantage of measuring GHG emissions directly at the source and may provide accurate and site-specific data for LCA. Climate sensors, on the other hand, monitor parameters such as temperature, humidity, and air quality, helping farmers optimize indoor housing conditions [37]. Additional technologies applied indoor include bedding moisture sensors, which assess hygiene conditions and support mastitis prevention while promoting animal comfort [38]. Whereas in outdoor systems, tools such as drones are employed to monitor animal location, pasture quality and farm infrastucture, while virtual fencing systems based on GPS collars, help contain animals within designated areas without the need for physical barriers [39].
3. From-Cow sensors: these advanced analytical tools focus on the biochemical analysis of animal-derived samples such as milk, hair, or feces (Table 3). Infrared spectroscopy (IRS) and mass spectrometry are employed to assess milk composition, identifying parameters like fat, protein, and somatic cell count (SCC), which are critical for both animal health monitoring and product quality assurance [40–42]. Blood and hair samples can provide long-term data on nutritional and stress levels, while feces analysis can reveal insights into digestive efficiency and overall health status [43].

1.5. Italian Mediterranean buffalo production

Buffaloes (*Bubalus bubalis*) are reared for its high-quality milk and meat and may serve as a source of draft power and leather. These

Table 1
Overview of At-Cow precision livestock farming technologies and their applications in buffaloes husbandry.

Reference	Breed	Country	Traits	Tool
[44]	Mediterranean	Italy	Identify estrus	Pedometer, NA, NA.
[45]	Surti	India	Identify estrus and ovarian activity	Heat detector, Hauptner, Germany.
[46]	Egyptian	Egypt	Identify estrus and ovarian activity	Draminski ® Electronics in Agriculture, Owocowa, Polland.
[47]	Murrah	Brazil	Identify estrus and ovarian activity	HeatWatch®, DDx, Incorporated, Boulder, Colorado, USA.
[48]	Mediterranean	Italy	Locomotor behaviour	Nikon d3200, Nikon Corporation, Tochigi, Japan +RumiWatch®, ITIN + HOCH GmbH, Bennwil, Switzerland.
[49]	NA	Brazil	Electronic identification	KT34/4, AnimallTAG, São Carlos, Brazil + subcutaneous transponder.
[50]	Nili-Ravi	Pakistan	Identify feeding, Rumination, Lying, and Standing behaviors	NEDAP®, Livestock Management, Groenlo, The Netherlands + Panasonic WV BP120, Panasonic, Bracknell, UK + Noldus Information Technology, 2004, Wageningen, The Netherlands.
[51]	Nili-Ravi	Pakistan	Monitoring calving	NEDAP®, Livestock Management, Groenlo, The Netherlands + Panasonic WV BP120, Panasonic, Bracknell, UK + Noldus Information Technology, 2004, Wageningen, The Netherlands.

multiple functions can play an important role in supporting rural livelihoods, enhancing agricultural sustainability, particularly in developing countries [73]. Global buffalo raw milk production has grown significantly, rising from 50 million tons in 1994 to 150 million tons in 2022, driven primarily by Asian countries (Fig. 1; [74]).

Indeed, according to FAO statistics, over 203 million buffaloes are raised worldwide, with approximately 98% of the total population reared in Asia ([74]; Fig. 2).

In contrast, only 0.20 % of the global buffalo population is found in Europe, with most of the population raised in Southern Italy. In this area, most of buffalo milk is transformed into 'Mozzarella di Bufala Campana PDO' (product with denomination of origin [75]). Over the previous 40 years, buffalo husbandry in Italy has undergone significant transformations, progressively adopting farming practices like those used in dairy cattle. As a result, Italian buffalo milk production has grown from 79,000 tons in 1994 to 254,000 tons in 2022 [74]. This growth has been driven by targeted selective breeding programs [76, 77], including higher culling rates to remove animals with low-performance, replacing them with the progeny of high-yielding animals. Productivity gains have also been supported by advancements in feeding strategies, improved housing conditions, and better overall herd management [75,67].

Although the practical adoption of PLF technologies in buffalo farming is still limited compared to their widespread use in dairy cattle, especially in Europe and North America, Italy represents a notable exception. Indeed, initial applications of PLF tools in Italy are modernizing buffalo farming practices. These experiences offer valuable insights into the potential of PLF application in buffalo husbandry and could serve as a reference for the development of similar approaches in other regions. In this context, PLF technologies may support the growing buffalo sector in developing countries, though their adoption remains constrained by limited economic resources [3]. Therefore, this review aims to assess the current state of PLF adoption in buffalo herd management, highlighting both the lessons learned from advanced systems and the opportunities for specific innovation in diverse global contexts.

A literature search was conducted in accordance with PRISMA guidelines using Scopus and Google Scholar. The search strategy employed Boolean combinations of the keywords: "buffaloes", "dairy buffaloes", "technology", "Precision Livestock Farming", "Precision Livestock Farming tool", "Precision Livestock Farming technology", "PLF tool", "PLF technology". The final search was performed in December 2024 and limited to articles published between 2000 and 2024. A total of 194 articles were retrieved from Scopus and 173 from Google Scholar. Articles were exported to an Excel file, and duplicates were removed. Studies were screened based on relevance for the review, and only those specifically addressing the application of PLF

Table 2
Overview of Near-Cow precision livestock farming technologies and their applications in buffaloes husbandry.

Reference	Breed	Country	Traits	Tool
[52]	Crossbred buffaloes	Philippines	Thermoregulatory response	Model SK-1250MC, Sato Keiryo-Seisakujyo, Japan.
[53]	Mediterranean	Italy	Milk production	DeLaval automatic milking system VMS 200, Tumba, Sweden.
[54]	Murrah	Brazil	Effect of estrous on vulvar, orbital area and muzzle temperature	Thermovisor E-40, FLIR, Oregon, USA + TWTG-2000, InstruTemp®, São Paulo, Brazil + MyLab™ FIVE, Genova, Italy.
[55]	Murrah	India	Scrotal surface temperature	FLIR®Systems, Oregon, USA.
[56]	Mediterranean	Italy	Early detection of subclinical mastitis	FLIR®Systems, Oregon, USA.
[57]	Mediterranean	Italy	Methane Emissions	Laser Methane mini™ (LMm) model, Tokyo Gas Engineering Co., Ltd., Tokyo, Japan.
[57]	Mediterranean	Italy	Distance between sensors and animal	DISTO D2 model, LEICA, Heerbrugg, Switzerland
[57]	Mediterranean	Italy	Measure temperature and humidity	RHT30 model, Extech, Nashua, USA.
[58]	Mediterranean	Italy	Quantify milk production	AFI-MILK®, TDM, San Paolo, Italy.
[59]	Mediterranean	Italy	Identify biometric parameters	D415 Depth camera, Santa Clara, USA + L515 LiDAR camera, Santa Clara, USA + RICOH ® WG–60 photo camera, Japan.
[60]	Mediterranean	Italy	Identify biometric parameters	D415 Depth camera, Santa Clara, USA. + L515 LiDAR camera, Santa Clara, USA + RICOH ® WG–60 photo camera, Japan.
[61]	Mediterranean	Italy	Measure milk production	DeLaval Automatic milking system, VMS 300, Tumba, Sweden.
[62]	Murrah	India	Early detection of subclinical mastitis	Darvi DTL007 camera, TAK Technologies Pvt. Ltd., Uttar Pradesh, India.
[63]	Mediterranean	Italy	Monitor milk production and quality	DeLaval Automatic milking system, VMS 300, Tumba, Sweden.

Table 3
Overview of From-Cow precision livestock farming technologies and their applications in buffaloes.

Reference	Breed	Country	Traits	Tool
[46]	Egyptian	Egypt	Quantify milk lactose	Lactoscan, Milkotronic, Bolgharia.
[64]	Mediterranean	Italy	Evaluate milk coagulation and acidity traits	MilkoScan™ FT6000, Foss Electric A/S, Hillerød, Denmark + Fossomatic FC, Foss Electric A/S, Hillerød, Denmark.
[65]	Mediterranean	Italy	Traceability	Fourier transform infrared spectroscopy (FTIR)
[66]	Mediterranean	Italy	Quantify milk somatic cell count-derived traits, fat, protein and lactose	MilkoScan™ FT6000, Foss Electric A/S, Hillerød, Denmark + Fossomatic FC, Foss Electric A/S, Hillerød, Denmark.
[67]	Mediterranean	Italy	Quantify milk somatic cell count-derived traits, fat, protein and lactose	MilkoScan™ FT6000, Foss Electric A/S, Hillerød, Denmark + Fossomatic FC, Foss Electric A/S, Hillerød, Denmark.
[68]	Mediterranean	Italy	Quantify milk somatic cell count-derived traits, fat, protein and lactose	MilkoScan™ FT6000, Foss Electric A/S, Hillerød, Denmark + Fossomatic FC, Foss Electric A/S, Hillerød, Denmark.
[69]	Mediterranean	Italy	Detection of alteration in buffalo milk	MilkoScan™ FT6000, Foss Electric A/S, Hillerød, Denmark + Fossomatic FC, Foss Electric A/S, Hillerød, Denmark.
[70]	Mediterranean	Italy	Subclinical mastitis and temperature	MilkoScan™ FT6000, Foss Electric A/S, Hillerød, Denmark + Fossomatic FC, Foss Electric A/S, Hillerød, Denmark + NASA Prediction of Worldwide Energy Resource (POWER) Data Access Viewer.
[71]	Mediterranean	Italy	Electrical conductivity and total and differential somatic cell count	CombiFoss 7 DC, Foss, Hillerød, Denmark.
[43]	Mediterranean	Italy	Chemical composition of feces and total-tract apparent nutrients digestibility estimated undigestible neutral detergent fiber or acid-insoluble ash	NIRS DS2500 instrument, FOSS Electric A/S, Hillerød, Denmark.
[72]	Mediterranean	Italy	Coagulation Traits	MilkoScan™ FT6000, Foss Electric A/S, Hillerød, Denmark + Fossomatic FC, Foss Electric A/S, Hillerød, Denmark.

technologies in dairy buffalo farming were retained. In cases where studies did not directly assess PLF tools in buffaloes, the technologies were instead evaluated for their potential applicability and relevance to buffalo farming systems. After applying inclusion and exclusion criteria, 119 studies were deemed eligible. Additionally, a keyword co-occurrence network analysis was performed based on the metadata of the selected articles (Fig. 3).

2. Applications of PLF technologies in buffalo species

Recent advancements reflect a growing interest in adapting PLF tools to the unique physiological, behavioral, and management characteristics of buffaloes. This section provides an overview of the main PLF technologies currently investigated or applied in buffalo farming, emphasizing their potential benefits for the sector, existing limitations, and key areas for further research development.

2.1. Identification and localization systems

Technologies for animal identification and tracking have become essential tools for the effective management of Italian Mediterranean buffalo herds, leading to optimized nutrition, health monitoring, and efficient reproductive performance [49]. A well-implemented animal identification system offers multiple benefits, including simplified herd management and, when integrated with accelerometers, the ability to collect valuable behavioral data such as lying, standing, and rumination patterns [30]. The most widely used identification systems in buffaloes, and those currently available, rely on radio frequency identification technology (RFID; [78]). This technology offers several advantages, as it allows for remote identification without the need for direct visual contact between the transmitter and receiver. The RFID sensors are typically deployed in the rumen as boluses, but they can be implanted subcutaneously or applied as ear tags. Usually, the signal transmitted by these passive transponders is captured by an antenna, and processed through specialized software. In addition, as in dairy cows, RFID sensors for buffalo are also developed using full-duplex and half-duplex technologies [79], which help overcome transmission distance limitations and minimize interference from metallic objects, whichcould disrupt the signal.

2.2. Genetic and genomic improvement through PLF technologies

Accurate individual recognition is essential for recording performance traits, forming the basis for robust data collection needed in genetic evaluations and selection. Building on this foundation, the integration of genomic technologies into buffalo breeding programs represents a significant step forward in accelerating genetic progress,

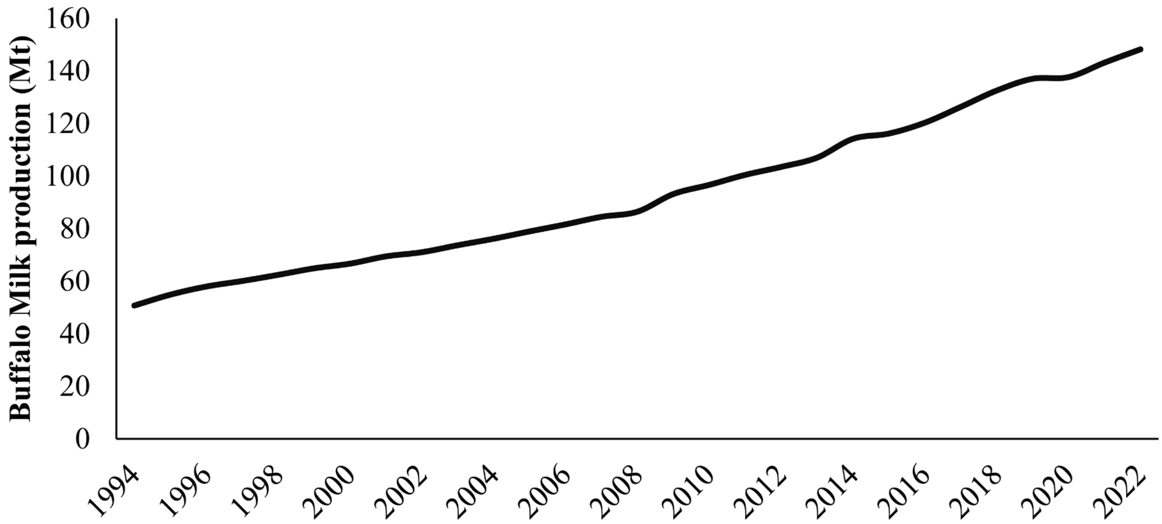

Fig 1. Global production of raw buffalo milk (in million tons) by year, from 1961 to 2021 [74].

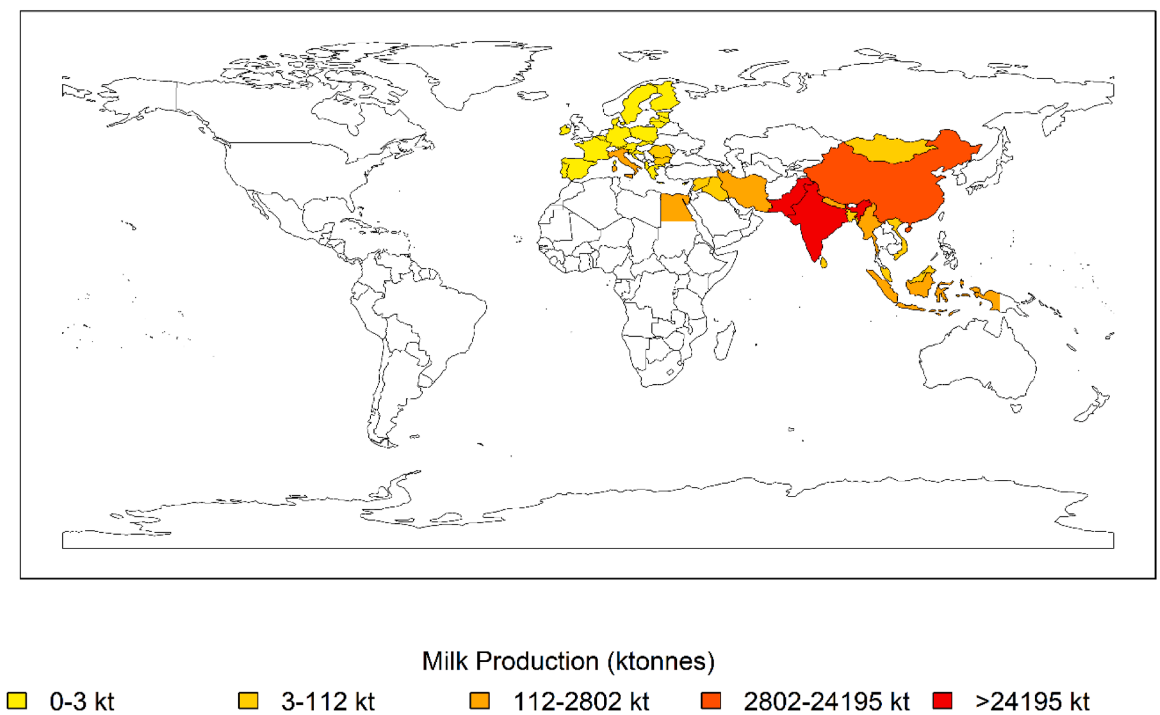

Fig 2. Raw buffalo milk production (in kilotons) by country in 2021 [74].

mirroring developments already well-established in dairy cattle [75–77]. Genomic selection relies on the estimation of breeding values based on genome-wide single nucleotide polymorphisms (SNPs), which are associated with economically important traits such as milk yield, reproductive performance, feed efficiency, and thermotolerance [80–83]. To translate genomic information into reliable selection decisions, advanced statistical models are required. Among these, the Genomic Best Linear Unbiased Prediction (GBLUP) approach has emerged as one of the most widely adopted methodologies, offering improved accuracy in the estimation of genomic breeding values [84, 85].

A major milestone in genomic selection for buffalo was achieved in 2013, when the Buffalo Genome Consortium completed the sequencing and assembly of the species' genome (GCF_000471725.1), leading to the development and validation of a 90 K SNP genotyping chip [86]. These advancements enabled the identification of quantitative trait *loci* associated with key productive and reproductive traits through genome-wide association studies [87,88]. These techniques have been applied to investigate traits such as milk yield [89–91], reproductive performance [88,92], and mastitis resistance [93]. Despite these advancements, the accuracy of genomic predictions relies on the quality of phenotypic data. Traditional methods of data collection often suffer from operator bias and limited measurement frequency. In this regard, PLF technologies offer a promising solution by enabling continuous, real-time, and objective phenotyping without the need for human intervention. These systems not only improve data reliability but also may support the integration of high-throughput phenotypic information into breeding programs. However, access to genomic data in buffaloes remains limited, primarily due to the high costs of genotyping, and further research is needed to expand its applicability at population level.

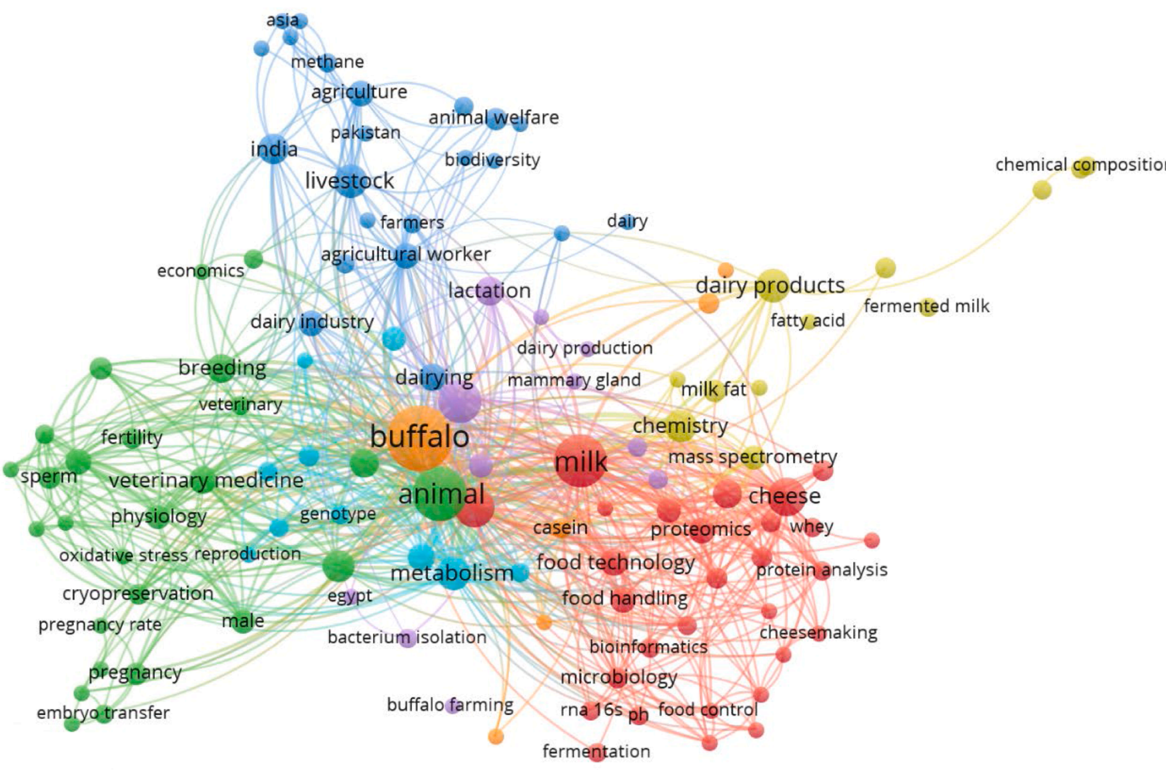

Fig 3. Network analysis based on bibliographic information of 119 selected papers* published between 2000 and 2024.
*Data was collected from Scopus (www.scopus.com) and Google Scholar (https://scholar.google.com/schhp?hl=it&as_sdt=0,5) in accordance with PRISMA guidelines. The search strategy employed Boolean combinations of the keywords: "buffaloes", "dairy buffaloes", "technology", "Precision Livestock Farming", "Precision Livestock Farming tool", "Precision Livestock Farming technology", "PLF tool", "PLF technology". The final search was performed in December 2024 and limited to articles published between 2000 and 2024. A total of 194 records were retrieved from Scopus and 173 from Google Scholar. All results were exported to an Excel file, and duplicates were removed. Studies were screened based on relevance, and only those specifically addressing the application of PLF technologies in dairy buffalo farming were retained. In cases where studies did not directly assess PLF tools in buffaloes, the technologies were instead evaluated for their potential applicability and relevance to buffalo farming systems. After applying inclusion and exclusion criteria, 119 studies were deemed eligible.

In parallel, advanced reproductive technologies such as sexed semen, artificial insemination, and embryo transfer, now widely adopted in the dairy cattle industry [94], are increasingly being introduced in buffalo farming. Although their application in buffalo is still relatively recent, preliminary results suggest they could reach levels of efficiency comparable to those achieved in dairy cows [95]. These technologies hold substantial potential to accelerate genetic progress and enhance the overall productivity of buffalo herds in both milk and meat production.

2.3. PLF technologies for automation and farm management

The adoption of AMS in buffalo farming is still limited compared to dairy cattle. A key limiting factor is the higher degree of variability in mammary gland conformation among buffaloes, which stems from the historically low selection pressure on udder morphology traits [96]. Modern AMS models are equipped with advanced positioning technologies, such as digital cameras, laser triangulation sensors, and time-of-flight cameras [61]. These systems enable accurate teats localization by estimating the distance to the udder surface through the measurement of the time an infrared light pulse takes to travel to the target and back [61]. Despite these improvements, the milking frequency and performance achieved in buffaloes remain slightly lower than those typically recorded in dairy cows [53]. The average number of daily milkings event using AMS in buffaloes ranges from 2.30 to 2.50, with milking time intervals between 9.60 and 10.4 hours. Early studies reported variable daily milk yields in buffaloes, with averages of 2.80 kg per milking (approximately 6.70 kg/day) and milking durations of around 8.30 min. More recent research has shown encouraging trends in productivity. For example, a study comparing two generations of AMS in buffaloes reported higher daily milk yields in the newer system (8.75 kg/day) compared to the previous model (7.11 kg/day) [61]. Similarly, a recent Italian study reported that buffaloes milked with AMS produced significantly more milk in respect to those milked using conventional methods [63].

While advancements in AMS have improved milking efficiency in buffaloes, PLF technologies have been applied in other management domains, such as the non-invasive evaluation of body condition and biometric characteristics. Notably, machine vision and 3D imaging systems have been successfully applied in Italian Mediterranean buffalo calves, enabling non-invasive measurement of body dimensions and accurate estimation of growth parameters [59,60]. In this context, three different types of imaging devices have been evaluated: a stereo depth camera (Intel® RealSense™ Depth Camera D415), a LiDAR depht camera (Intel® RealSense™ LiDAR Camera L515), and a standard 2-dimensional digital camera (RICOH® WG-60). Among these, the LiDAR camera showed the most accurate results, with measurement errors of less than 5.00 mm at a distance of 1.00 m and less than 14.0 mm at 9.00 m, when operating at Video Graphics Array resolution (VGA) and under high reflectivity conditions (95 %). These findings confirm the potential application of LiDAR technology as a in-line morphometric assessments tool. Nonetheless, several challenges were reported in practical applications. Both the stereo and LIDAR cameras faced difficulties in acquiring clear and consistent images of buffaloes due to their dark coats, which reduces light reflectance. Additionally, external factors such as variable lighting conditions and airborne dust, negatively affected image quality, limiting the performance of these systems in real farm environments [59]. The same PLF technology has also been applied to measure the volume and weight of dietary concentrates, with the LiDAR camera enabling digital reconstruction of the feed mass in the manger and achieving over 98 % accuracy [97]. Such technological advancements represent a significant step forward in the objective quantification of feed intake, offering new opportunities to optimize feeding management and enhance production efficiency.

2.4. Monitoring of reproduction through PLF technology

In addition to applications in feeding and growth monitoring, reproductive management in dairy buffaloes represents one of the most advanced and explored areas for the use of PLF technologies. For instance, automated estrus detection systems, which monitor behavioral and physiological changes during the estrous cycle, have been developed and tested in buffaloes [98]. These systems generate individual heat alerts based on parameters such as movement, mounting activity, and restlessness. However, their reliability can be limited by the occurrence of false-positive detections [98,99]. For this reason, alerts typically require validation through gold-standard methods such as progesterone assays. To improve accuracy, some studies have explored the integration of multiple sensors, combining different types of physiological and behavioral data [100]. Non-invasive wearable sensors, applied to the neck, ears, or limbs, have become widely adopted in dairy cattle, but their use in buffaloes is still relatively limited. Early efforts to use pedometers for estrus detection in buffaloes date back to the early 2000s [44]. These systems reported a conception rate of approximately 40 % and an average of 1.30 artificial inseminations per conception. Reduced performance was attributed to species-specific reproductive traits, such as double estrus behavior observed in about 8 % of animals over a 48-hour period, and estrus-like activity in 25–30 % of females with high progesterone levels or pregnancy.Among estrus behavioral indicators in buffaloes, mounths are considered the most definitive signs. Mounts can be monitored automatically using pressure-sensitive technologies attached to the tailhead. Studies using pressure-sensitive telemetry devices (Heat Watch®, DDX Inc, Colorado, USA) were conducted in Brazil [47]. These devices were activated by the pressure of a mounting herd mate sustained for at least two seconds. The system transmited data, including time, date, and identification of the mounted animal, to a receiver and then to a computer for analysis. Estrus was confirmed when an animal was mounted at least three times within a four-hour period, achieving a sensitivity of 90 % [47].

More recently, infrared thermography (IRT) has been investigated as a non-invasive tool for reproductive monitoring. Vulvar surface temperature has been shown to increase during estrus and correlates with serum progesterone levels, making it a reliable indicator of reproductive phase [54]. In contrast, surface temperatures of the muzzle and orbital regions did not consistently reflect estrous status but were instead associated with rectal temperature and environmental conditions. The same technology has also been employed in buffalo bulls, where testicular thermography, using devices such as FLIR i5® (FLIR Systems, Wilsonville, Oregon), has proven usefull in assessing the effects of heat stress and environmental factors on semen quality [55]. However, limitations remain due to skin thickness and external conditions such as ambient temperature, which affect measurement sensitivity and specificity. To avoid any BIAS, selecting the appropriate thermal window (e.g., orbital, nasal, mammary, or urogenital) is critical to minimize external interference and ensure accurate physiological interpretation. Another promising technology consists in the monitoring of vaginal electrical resistance, which increases during estrus due to elevated vaginal mucus volume and ionic content [45,46]. Although this method offers precise timing for insemination, its applicability is limited by the need for frequent animal handling and the lack of automation.

Calving monitoring also benefits from PLF technologies. For example, automated systems like NEDAP® (Nedap Livestock Management, Groenlo, The Netherlands) can monitor behavioral changes preceding parturition [51]. In buffaloes, the system detected a significant reduction in feeding time (from 220 to 181 min/day) and rumination time (from 559 to 443 min/day) within 24 hours before calving. Simultaneously, lying time increased (from 532 to 665 min/day), as did the number of steps taken (from 1672 to 2314 steps/day), indicating a marked shift in activity patterns. In conclusion, while several PLF technologies show great potential for improving reproductive management in buffaloes, their effectiveness remains limited by species-specific anatomical and physiological traits, environmental variability, and practical or economic constraints, particularly because most of these tools are originally developed for dairy cattle and only later adapted to buffalo systems.

2.5. Health monitoring in buffalo herds through PLF technologies

Numerous studies on dairy cows have linked alterations in physiological functions to the onset of metabolic or physiological disorders [101,102]. Achieving effective health monitoring requires the assessment of key behaviors such as feeding, lying, walking, and ruminating along with physiological activities. Recent studies have validated the application of PLF technologies for health monitoring in buffaloes. As mentioned earlier, Quddus et al. [50] evaluated the effectiveness of the NEDAP® monitoring system in tracking essential behaviors such as feeding, rumination, lying, and standing in buffaloes, comparing its performance against visual observation and video recordings. The NEDAP® technology proved to be highly reliable, showing a strong correlation (ranging from 0.85–0.91) between sensor data (NEDAP® and video recording) and human visual observations, with the highest accuracy recorded for rumination and standing activities. Similarly, three-dimensional accelerometers (RumiWatch® pedometer, ITIN + HOCH GmbH, Bennwil, Switzerland), originally designed to monitor rumination and chewing behavior in cattle, have also been evaluated for their potential to assess locomotor activity in buffaloes when positioned on the hind limbs, near the fetlock joint [48]. This technology was used to develop an algorithm capable of accurately identifying standing, lying, walking time, and the number of strides taken by buffaloes. The system demonstrated a sensitivity exceeding 99 %, with an error rate below 10 %, indicating the groundwork for further research. These findings were supported by a recent trial conducted on Italian Mediterranean buffaloes [103], although significant variability was observed among individual animals.

As part of broader health monitoring strategies, udder hygiene plays a crucial role in dairy production systems, given its direct impact on mastitis prevention, animal welfare, and overall farm profitability [62,104–106]. Automated cleanliness evaluation systems, based on image processing system, have been developed to assess the hygienic status of udder in cows [104]. Although buffaloes have historically been considered less susceptible to mastitis than dairy cows, increasing evidence points to a rising prevalence of subclinical intramammary infections [66,68]. This highlights the need for continuous and automated health monitoring, which PLF technologies may help to address [62,106]. Milk yield decreases as somatic cell count (SCC) increases[107]. For example, Costa et al. [66] reported that buffaloes with SCC below 140,000 cells/mL produced about 1 kg more milk per day than those exceeding 500,000 cells/mL. Beyond SCC, differential somatic cell count (DSCC), which reflects the proportion of neutrophils and lymphocytes within total SCC, has emerged as a more sensitive tool for early mastitis detection [70,71]. In buffaloes, DSCC values typically range between 43.8 % and 60.5 %, peaking around early lactation. Recent developments in PLF include machine learning algorithms capable of predicting mastitis by integrating key parameters such as milk yield, SCC, DSCC, and milk electrical conductivity (EC), collected during the month prior to diagnosis [70]. Importantly, DSCC has shown moderate heritability [108,109]. Milk EC is another PLF-compatible trait with proven value in mastitis detection. Inflammation compromises the blood–milk barrier, increasing sodium and chloride concentrations while decreasing potassium, thereby altering EC values [110]. Despite the influence of physiological factors like parity and days in milk, EC remains a reliable indicator of subclinical mastitis in buffaloes [58]. Matera et al. [58] observed that a one-unit increase in EC was associated with a drop of more than 0.50 kg/day in milk yield and proposed a predictive model using EC values recorded on days 1, 3, and 5 before test-day to anticipate udder health issues. In this context, infrared thermography (IRT) is another promising PLF application for udder health monitoring. Sarubbi et al. [56] demonstrated a strong correlation ($R^2 = 0.64$) between udder surface temperature and SCC in buffaloes with experimentally induced mastitis. Moreover, *pre*-milking thermal imaging showed high diagnostic sensitivity and specificity (respectively 0.80 and 0.91), with morning scans yielding better performance than evening ones [106]. Consistently, Gayathri et al. [62] reported that elevated udder surface temperatures in quarters with infections tend to normalize by evening due to the immune response. While these advancements highlight the potential of PLF technologies in improving udder health monitoring in buffaloes, their practical implementation, particularly in low- and middle-income countries, remains constrained by factors such as cost of infrastructure, and lack of operator traininng.

Beyond udder health, the monitoring of internal physiological parameters represents a promising yet underexplored area in buffaloes. Several PLF tools successfully implemented in dairy cattle, such as intraruminal boluses for tracking ruminal temperature, pH, and activity [31,32], have not yet been validated in this species. Integrating these technologies into buffalo farming could provide valuable data on digestive efficiency and metabolic stress, further supporting health management and welfare assessment.

2.6. Environmental control through PLF systems - influences on buffalo welfare

Environmental conditions significantly influence animal welfare and productivity, with the temperature-humidity index (THI) serving as a key indicator for assessing thermal stress. Buffaloes are vulnerable to heat stress due to their specific dark skin and reduced number of sweat glands, which limit heat dissipation [52,111]. Several studies have reported that THI values above 71 can trigger physiological stress responses in buffaloes, including altered cytokine expression, oxidative imbalance, and changes in SCC [37,105]. Although traditionally considered more tolerant to high temperatures than cattle [111], recent studies have also highlighted their sensitivity to cold stress, with milk yield declining when THI falls below 59 [112]. This sensitivity to both heat and cold is particularly relevant in production contexts characterized by cold temperatures during winter and hot, humid conditions in summer. For instance, in Italy, seasonal breeding strategies are used to concentrate calvings in winter months to match the spring–summer demand for mozzarella [76,113,114], which exposes animals to low temperatures during physiologically vulnerable stages such as early lactation. In this context, PLF technologies offer concrete opportunities to improve the management of environmental stress. The development of sensor-based systems able monitor temperature and humidity, combined with real-time THI alerts, may allow for timely interventions such as adjusting ventilation, shade, heating, or feeding schedules. In parallel, the integration of physiological monitoring, such as heart rate, respiratory rate, and blood oxygen saturation, can provide a more complete and dynamic assessment of animal responses to thermal stress [115, 116]. Although still limited in livestock, the development of automated systems to measure these physiological parameters in buffaloes could significantly enhance welfare monitoring, especially in extreme climates. This becomes even more crucial as climate change intensifies temperature fluctuations and environmental stressors.

Reducing methane emissions from livestock has become an increasingly important area of research, and PLF technologies can support this goal by enabling the monitoring of emission patterns and identifying critical sources within the production system. Various methods have been developed to estimate methane emissions, including metabolic chambers [117], GreenFeed systems [118], and methane sensors integrated into AMS [119]. Among these solutions, the laser methane detector (LMD) is one of the few PLF tools that have been applied in buffalo herds [120]. While the accuracy of LMD measurements is relatively limited, the device provides a rapid, non-invasive method of assessing methane emissions under field conditions. In growing buffaloes, daily methane emissions measured using LMD were estimated at 329 ± 160 g/day, corresponding to approximately 120 ± 58.4 kg/year [57]. Notably, methane emission intensity was found to be highest during summer compared to winter, likely due to the additional physiological burden imposed by elevated THI values in warmer months [57]. In addition, studies conducted on lactating buffaloes demonstrated that LMD is capable of distinguishing between baseline respiratory methane emissions and peaks associated with eructation events [103]. Nonetheless, the practical on-farm use of LMD requires methodological standardization, including clear operating protocols to reduce subjectivity and enhance reliability. While systems such as GreenFeed and respiration chambers offer greater precision, they are not yet applied in buffaloes, and interoperability between measurement tools remains limited.

Tools such as geostatistical mapping and vegetation indices have been used to estimate forage availability and support optimized grazing strategies. For example, Valente et al. [121] demonstrated that areas with soil pH values below 4 were associated with reduced forage yield, and that dry matter and green matter availability could be effectively predicted using remote sensing and geospatial data. One of the most interesting innovations in this area is virtual fencing, which enables precise control of grazing behavior through non-physical boundaries [39]. This system typically relies on GPS-enabled collars that deliver an auditory warning followed, if necessary, by a mild electric stimulus when an animal approaches or crosses a virtual boundary set by the farmer. However, while virtual fencing has shown promise in cattle and sheep, it has not yet been formally tested in buffaloes. Several potential limitations must be considered before implementation in this species. These include the possible presence of predators, which may necessitate physical barriers for animal safety, and the fragmented nature of many pasture areas, which may complicate the definition and maintenance of virtual boundaries. From an animal welfare perspective, concerns have been raised about the ethical implications of delivering electric *stimuli*, even at low intensities, particularly for animals repeatedly attempting to cross the boundaries. Additionally, drones have emerged as a complementary tool for pasture monitoring and livestock tracking, offering real-time aerial surveillance and data collection over large grazing areas. Although promising, the integration of drones into daily grazing management is still in its early stages, and there is a lack of studies evaluating their impact on animal behavior and stress responses, particularly in buffaloes. Some drone models emit considerable noise, which could potentially disturb or stress the animals. Overall, while these technologies present exciting opportunities for more precise and sustainable pasture management, their adaptation to buffalo production systems requires careful validation, consideration of species-specific behavior and welfare.

2.7. Monitoring animal-based product quality through PLF

Among the PLF technologies aimed at improving milk quality assessment IRS, particularly near-infrared (NIRS) and mid-infrared (MIRS) techniques, has gained increasing relevance in buffalo farming due to its speed, non-invasive nature, and cost-effectiveness [122,123]. Although originally developed for dairy cattle, these tools have been adapted for buffalo milk, which differs significantly in composition, particularly in fat and protein contents [67]. As a result, bovine-based models have served as a foundation for developing calibration curves tailored to buffalo milk [65,69]. Moreover, Guerra et al. [72] reported moderate accuracy using MIR spectroscopy for predicting curd firmness in bulk buffalo milk, confirming its potential as a preliminary screening tool. Similarly, Manuelian et al. [124] demonstrated the effectiveness of MIR in classifying non-coagulating samples, achieving 91.6 % accuracy in the calibration set and 67.9 % in validation. Yao et al. [125] showed that MIR-based models coupled with machine learning accurately predicted key fatty acid profiles in buffalo milk, demonstrating the value of this approach for product quality monitoring. Beyond phenotypic screening, IRS-derived data could be leveraged for genetic selection, as demonstrated in dairy cattle, where spectral traits have been successfully integrated with genomic information to accelerate genetic improvement. Applying similar strategies in buffalo breeding may contribute to more efficient production systems and long-term sustainability.

3. Conclusions

Precision Livestock Farming technologies offer promising opportunities to enhance the sustainability, efficiency, and resilience of buffalo production systems. Evidence from European and North American dairy cattle systems has shown how the gradual adoption of such technologies can lead to significant improvements in productivity, animal welfare, and environmental monitoring. In the case of buffalo farming, initial experiences, particularly from Italy, have demonstrated the potential of PLF to modernize traditional practices and improve overall herd management. While these developments have occurred primarily in technologically advanced countries, their potential relevance may extend to regions where buffalo farming plays a central role in rural livelihoods, particularly in countries of Asia and Africa. Our review, however, did not identify specific studies documenting the implementation of PLF tools in buffalo systems within these regions. This gap underscores the need for further research and for solutions that are context-specific, considering local socioeconomic conditions, infrastructure availability, and technical capacity. In low- and middle-income countries, the direct transfer of advanced PLF systems developed in Europe or North America may not be immediately feasible or appropriate, as local priorities often focus on improving food security and access to animal-source foods, objectives that may precede investments in advanced welfare or environmental monitoring technologies. In such contexts, the adoption of PLF requires a balanced and progressive approach. Beginning with affordable, accessible tools, such as mobile-based data collection systems, basic monitoring sensors, or reproductive tracking platforms, may offer viable entry points for innovation. When adapted to the local context and supported by training, extension services, and institutional engagement, these tools can help establish the foundations for more data-driven and resilient buffalo farming systems. Ultimately, the long-term success of PLF in diverse production environments will depend not only on the availability of appropriate technologies, but also on sustained investment in capacity building, inclusive innovation policies, and the active involvement of local stakeholders. This review aims to inform stakeholders by examining current applications and future prospects of PLF in buffalo farming, fostering a more inclusive perspective on its global sustainability potential.

Ethics statement

The approval of the Animal welfare and use of Committee was not required for this study.

Declaration of generative AI in scientific writing

The manuscript was not authored with the assistance of artificial intelligence (AI).

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CRediT authorship contribution statement

Roberta Matera: Writing – review & editing, Writing – original draft, Conceptualization. **Federica Pierro:** Writing – review & editing, Visualization. **Matteo Santinello:** Writing – review & editing, Methodology, Investigation. **Antonio Iraci Fuintino:** Validation, Conceptualization. **Giovanmaria Pacelli:** Visualization, Software. **Tomas Norton:** Writing – review & editing, Investigation, Conceptualization. **Gianluca Neglia:** Writing – original draft, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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