Integrating digital phenotyping and genomics: Unraveling cattle behavior through sensors and genomic data

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Summary
This paper reviews the integration of digital phenotyping and genomics in dairy cattle farming, focusing on sensors such as automated milking systems (AMS), collars, and pedometers for behavioral and physiological monitoring. Sensor-based traits, including milking behavior, rumination, activity, and feeding patterns, exhibit moderate heritability (0.09–0.42), highlighting their suitability for selective breeding. Incorporating these real-time data into breeding programs could significantly enhance cattle welfare, health monitoring, and overall farm productivity.

Key words: selection, breeding program, genomics, phenotyping, sensors, precision livestock farming

Introduction
The global livestock industry is currently undergoing a significant transformation, driven primarily by the widespread adoption of Precision Livestock Farming (PLF) and, in particular, new digital phenotyping techniques (Brito et al., 2020; Kleen and Guatteo, 2023; Koltes et al., 2019; Menezes et al., 2024). This transformation is particularly relevant nowadays, while addressing concerns about global population growth. According to United Nations projections, the world's population is expected to reach 10 billion by 2050 (UN report, 2017). To adequately feed this expanding population, agricultural productivity must increase by approximately 70% (Fraser & Campbell, 2019). Digital phenotyping, which employs sensors and wearable technologies analysed using advanced artificial intelligence (AI) algorithms - enables comprehensive monitoring of cattle behaviour and physiological conditions. Such advancements represent a new shift in livestock management practices (Pedrosa et al., 2024; Neethirajan, 2023; Menezes et al., 2024; Mayberry et al., 2023) and offer a promising strategy for meeting the increasing demand for agricultural productivity. Sensor technologies currently employed in cattle farming, including accelerometer-based collars, pedometers, and automated feeding and milking systems, enable continuous, non-invasive monitoring of animal behavior (Lamanna et al., 2025). These sensors provide real-time data on locomotion patterns, rumination, feeding behavior, and social interactions, significantly improving the accuracy of predicting estrus or health conditions such as lameness or metabolic disorders, and typically those are incorporated in some of the farm management solutions. Another highly promising

technology that will play important role in animal production is video surveillance. Video surveillance with regular 2D cameras, depth cameras, or even 3D vision can be used to automatically observe cow behavior and body posture without attaching devices to the animal (Menezes et al., 2024). Computer vision algorithms can analyze video feeds to identify individual animals and monitor behaviors such as feeding, lying, or social interactions. Thermal infrared cameras provide a heat map of the animal, enabling remote measurement of body surface temperatures. This helps detect signs of fever or inflammation early, for instance, a thermal camera can highlight a hoof with higher temperature due to hoof infection. Besides, environmental sensors placed around barns track temperature, humidity, and gas levels to assess the micro-climate cattle experience (Lamanna et al., 2025). Monitoring barn temperature-humidity index in real-time helps manage heat stress, which can impact feed intake and fertility. However, in the context of animal breeding and selection, where traits with economic value are main targets, all this information obtained from various sensor technologies was usually neglected. Besides, this data is highly complex, incompatible between different countries, farms etc. Despite the significant technological advances, breeding programs predominantly rely on static variables such as milk yield, fat and protein content, and somatic cell count. Although genomic selection has notably increased genetic progress by integrating DNA information with phenotypic records, incorporating real-time data into breeding schemes presents both significant opportunities and challenges. These include handling vast volumes of data, standardizing phenotypic definitions across different technologies, and accurately estimating genetic parameters for novel sensor-derived traits. Besides, the integration of these technologies could also improve animal welfare mainly as these approaches are safe and non-invasive, which is additional benefit in future farm management practices (Brito et al., 2020). The objective of this review is to summarize the current knowledge on PLF technologies in cattle breeding sector and discuss their potential integration with genomic selection in future breeding strategies. Overcoming technical, economic, and practical barriers will be essential to fully capitalize on these technological advances, ultimately shaping the future of dairy cattle sector (Pedrosa et al., 2024; Brito et al., 2020).

Early scientific studies

One of the first scientific reports of using sensors for measuring activity on dairy cows dates back to the 1950s. Farris (1954) strapped a pedometer (a flat wooden block with a metal cover and leather leg strap) to cows' hind legs to record steps, demonstrating that cows exhibit increased walking activity during estrus. In Farris's study on 13 Guernsey cows, most animals showed a marked rise in step-count for 24–48 hours around estrus. This was the earliest evidence that measuring a cow's physical activity could help indicate heat (estrus). Two decades later, Kiddy (1977) published a study in Journal of Dairy Science using modern pedometers on 40 cows to quantify activity changes at estrus. The study confirmed that cows were 2.8–4 times more active during estrus compared to other periods, and suggested that pedometer-recorded activity peaks could be used to decide optimal timing for insemination (Kiddy, 1977; Eckelkamp, 2019). This 1977 study was the first to explicitly propose pedometer monitoring as a practical aid for estrus detection on dairy farms. Subsequent research in the 1980s further confirmed correlation between activity levels and estrus (Lewis and Newman, 1984) while also expanding the use of pedometers beyond fertility. In later years, pedometers were additionally tested for detecting health issues such as early lameness by analysing drops in daily step counts (Mazrier et al., 2006). Wearable neck sensors or collars for monitoring cattle behavior or physiology also began to appear in the literature by the 1980s. An early example is the work of Luginbuhl et al. (1987), who developed an electronic halter collar with a pressure sensor to monitor chewing cycles in stall-fed cows. Their system used a flexible noseband with embedded electrodes that detected jaw movements by changes in electrical

resistance as the cow chewed. This allowed automatic recording of eating and rumination behavior, demonstrating one of the first collar-based sensors for dairy cattle physiology. Around the same time, researchers also experimented with acoustic and motion sensors on collars to record grazing or ruminating activity (e.g. a microphone on the collar to capture cud-chewing sounds) (Hoffmann et al., 2024). These 1980s studies proved that collar-mounted sensors (whether pressure transducers or microphones) could reliably track bovine behaviors like feeding and rumination. By the 1990s, accelerometers and other electronics became smaller, leading to trials in which motion sensors were placed on collars to detect various cattle behaviors. Nevertheless, the earliest scientific applications of collars in dairy cattle were focused on monitoring ingestive behavior and activity, laying the groundwork for today's multi-sensor smart collars.

First commercial uses

The transition of pedometer technology from research to farms occurred by the late 1970s and early 1980s. In Israel, the Afikim (Afimilk) company developed the first commercial heat/estrus detection pedometer for dairy cows around the early 1980s. This electronic pedometer, attached to a cow's leg, counted steps and interfaced with herd management software, alerting farmers to increased activity associated with estrus. By the mid-1980s, such pedometer systems were being adopted in dairy herds for automated estrus detection. For instance, early on-farm trials showed pedometer-based systems could raise heat detection rates above traditional visual observation levels (Senger, 1994). Throughout the 1990s, similar on farms systems became more widespread globally, and companies like Nedap and DeLaval integrated activity meters into their milking and herd management systems. DeLaval's ALPRO system (1990s) could read leg-mounted activity counters via radio every hour, and report cows with activity spikes for breeding (Brehme et al., 2006). Thus, by the late 20th century, pedometers became an established precision dairy tool for estrus detection on commercial farms. In the 2000s, farmers and vets also began using pedometer data for secondary applications such as identifying lame cows that walk less (Mazrier et al., 2006), but estrus detection was the initial driving force of on-farm pedometer adoption. Widespread on-farm use of wearable neck sensors took hold slightly later, as the technology matured in the 2000s. One of the first commercial products was the SCR Heatime, introduced by SCR company (also from Israel). SCR engineers developed their first cow collar tags in 1998, and by 2006 began mass-marketing these collars globally. The SCR collar (often called a "tag") contained motion sensors and later combined with microphone. It could transmit data wirelessly to detect heats via increased activity and (in newer versions) monitor rumination via chewing sounds (Bar and Solomon, 2010). After its 2006 launch, SCR's Heatime quickly became one of the most popular commercial heat detection solutions worldwide (Press release, 2014). Farmers, from New Zealand pasture operations to large-scale US dairies, adopted it to continuously track each cow's activity and health. Around the same time, other companies launched similar smart collars, Allflex and Afimilk (in the 2010s) released collar devices that monitor rumination, feeding, and activity. By 2010, many progressive dairies were using collars to not only detect estrus but also to catch early signs of illness or stress, since rumination minutes and activity patterns often change when a cow is sick or heat-stressed. It's worth noting that an even earlier use of collars in dairy farming was electronic identification (RFID) neck collars in the 1980s, which allowed automated feeding and milking systems to recognize individual cows (Prasad, 2023). However, those served primarily as ID tags. The first collars with true behavioral/physiological sensors became commercially viable in the early 21st century, culminating in today's smart collars that are an integral part of precision dairy management (Lamanna et al., 2025). Overall, pedometers have been used in dairy cattle research since the 1950's and saw farm adoption by the 1980s mainly for estrus detection, while sensor collars emerged in research by the late 1980s and reached

commercial farms by the 2000s, expanding monitoring to rumination, feeding, and health. These technologies, initially tested in labs and universities are now common on modern dairy operations, where they continue to evolve as invaluable tools for monitoring cow behavior and physiology. If the main target is to include activity data in breeding programs with aim to genetically select cattle with more desirable traits, the following step is to carefully design these new phenotypes and to develop their standards.

Current breeding programs with classical phenotypic and genomic data

Traditional animal breeding programs have usually focused on a set of static performance traits that are recorded intermittently. In dairy cattle, for example, national selection indices (such as the Lifetime Net Merit in the U.S. or the TPI) heavily weight milk production (milk yield and fat/protein content in standardized 305-day lactations), along with traits like fertility (e.g. calving interval or conception rate), longevity, and udder health (often indicated by somatic cell count) (Wiggans and Carrillo, 2022). These phenotypes are typically measured during routine testing or evaluations, for instance, milk yield and components are measured monthly or bimonthly on dairy farms, and somatic cell count is checked in milk samples as a mastitis indicator. In beef cattle, important recorded traits include weaning and yearling weights, feedlot gain, carcass quality measures, and calving ease. Historically, such data were collected manually or via periodic weigh-ins and then used in genetic evaluations. Additionally, traditional selection relied on pedigree-based estimated breeding values (EBVs), and the rate of genetic progress was constrained by the accuracy and availability of these phenotypic records. Traits like milk yield are moderately heritable and could be improved steadily, but many health or fertility traits are lowly heritable and hard to measure, thus received less direct selection emphasis. Because observations were not continuous, important aspects of animal performance, like how an animal behaves or copes day-to-day remained unrecorded in breeding programs (Neethirajan and Kemp, 2021). This meant that breeding decisions were based on a snapshot of an animal's performance (e.g. an average lactation yield or a single classification score for conformation) rather than the full spectrum of its behavioral or physiological profile.

The adoption of genomic selection in the past 15 years has dramatically enhanced breeding programs by integrating DNA information with phenotypic data. Genomic selection uses dense genetic maps of single nucleotide polymorphisms (SNPs), usually ~50k markers across the genome to predict an animal's genetic merit, allowing selection decisions to be made early in life with improved accuracy (Brito et al., 2020). In dairy cattle, genomic evaluations were widely implemented around 2008–2010, and since then the rate of genetic gain has roughly doubled (Wiggans and Carrillo, 2022). For example, the U.S. Holstein breeding program saw annual gain in net merit (a composite index in economic $) increase from about $40 before genomics to about $85 after genomics was introduced (Wiggans and Carrillo, 2022). This jump is attributed to the ability to select young bulls and heifers based on genomic breeding values that have accuracy comparable to having several lactations of progeny data. The impact on genetic progress has been profound: shorter generation intervals and more accurate selection mean faster improvement in milk yield, feed efficiency, and even harder-to-improve traits like fertility. Moreover, genomic selection has facilitated the inclusion of new traits into breeding objectives. Because thousands of animals are now genotyped and their DNA was used to predict traits, breeders have started to incorporate traits that were previously ignored due to limited data. For instance, many dairy populations now evaluate traits such as heifer fertility, calving ease, stillbirth rate, and even health disorders (e.g. mastitis, lameness, metritis) using producer-recorded event data combined with genomics. The U.S. dairy evaluation now formally includes over 50 traits, having added fertility traits (age at first calving), longevity (cow livability), calving traits, six common health disorders, feed efficiency (residual feed intake), and even

gestation length in recent years. Genomic selection enabled these additions by providing the statistical power to estimate breeding values even for traits with sparse or binary phenotypes, as long as a reference population with phenotypes and genotypes exists. The net result is that current breeding programs are increasingly multi-trait, aiming for balanced improvement. For example, Nordic dairy breeding programs include an index of health and fertility traits alongside production, and beef breeding programs consider temperament scores or feed intake measures if available. However, even with these expansions, the phenotypic data used in genetic evaluations today are still largely intermittent, manually collected measures (like veterinary recorded disease events or monthly production) rather than continuous behavioral or physiological metrics. Integrating rich activity data (behavioral and physiological) from sensors into existing breeding programs poses several challenges. One major hurdle is data standardization and management. Traditional breeding databases handle relatively low-frequency records (e.g. one lactation yield per cow per year, or a few disease events per cow) and are not designed for streaming data. In contrast, a single sensor-equipped cow could generate thousands of data points per day (activity counts, position coordinates, etc.), creating a massive amount of information unused in current genetic evaluations (Koltes et al., 2019). Breeding organizations would need new infrastructure to store, curate, and preprocess this big data so that it can be distilled into meaningful phenotype or trait values (for example, summarizing a cow's daily step count into a monthly "activity level" trait). Therefore, this explained challenge refers to phenotype definition - translating raw sensor readings into reproducible phenotypic traits suitable for selection. While it is straightforward to define traditional traits (like 305-day milk yield), it is less obvious how to define a "behavioral trait" from continuous sensor data. Researchers must decide whether the "average daily lying time" or lying bout are the relevant heritable metrics to use for genetic analysis. This requires extensive validation to ensure these derived traits are biologically meaningful and have sufficient genetic variation. Early attempts have shown that many sensor-based measures do have genetic variability, but reaching consensus on trait definitions is ongoing. Another challenge is data compatibility and scale across farms. Different farms may use different brands of sensors with different calibrations or have different management that influences behavior data. For breeding use, data from many herds must be comparable, which might require standardizing outputs from various devices or developing robust genotype-by-environment models. Another major challenge is standardization. Furthermore, not all farms currently use sensors, potentially biasing which animals have rich phenotype data. Often these are elite herds or research farms that invest in advanced monitoring, which could lead to a biased sample if used directly in breeding value estimation. Breeding programs must be cautious in integrating such data or find ways to encourage broader farmer participation in data collection. There are also concerns about the heritability and economic value of these novel phenotypes. Breeders are accustomed to traits like milk yield (highly heritable and directly tied to income) or SCC (moderate heritability, tied to mastitis costs). But for a trait like "daily step count variability" or "rumination time", the heritability might be low or unknown, and the economic value is indirect. It remains challenging to convince industry stakeholders to include a new trait in a selection index unless its genetic parameters and impact on profitability are well understood (Behren et al. 2023). Lastly, technical and logistical issues such as handling massive datasets and computational load must be resolved. National genetic evaluations are already computationally intensive with millions of animals; adding high-frequency phenotypes could require new statistical models (e.g. random regression models to handle longitudinal data) and greater computing resources. In summary, while current breeding programs have successfully incorporated genomic data and expanded trait goals, they are only beginning to scratch the surface of using real-time behavioral and physiological data. Bridging this gap will require addressing data pipeline issues and demonstrating that these new phenotypes can be reliably

measured at scale and will improve selection decisions. Table 1 provides examples of heritability estimates reported for sensor-based traits in cattle.

Table 1. Heritability of activity-related traits in dairy cattle (wearable sensors and automated milking system)

Rumination time (min/day)	Collar (chewing sensor)	0.34	0.05	Moretti et al., (2018)
Lying time (hours/day)	Leg/Collar accelerometer	0.37	0.07	Nascimento et al., (2024)
Step count (steps/day)	Pedometer (activity tag)	0.19	0.06	Nascimento et al., (2024)
Feeding time (min/day)	Collar (eating time sensor)	0.23	0.03	Cavani et al., (2022)
Activity time (min/day active)	Collar (motion/active time)	0.14	0.02	Lemal et al., (2024)
Milking frequency (milkings/day)	AMS[1] robot logs (voluntary)	0.23	0.04	Aerts et al., (2021)
Milking speed (kg/min)	AMS (milk flow rate)	0.42	0.07	Aerts et al., (2021)
Milking duration (min/visit)	AMS stall time per milking	0.19	0.07	Santos et al., (2018)
Milking refusals (count/day)	AMS (robotic refusal events)	0.09	0.01	Pedrosa et al., (2023)
Milking interval (hours)	AMS (time between milkings)	0.07	0.03	Santos et al., (2018)

[1]automated milking system

Table 1: Examples of heritability estimates for novel sensor-derived or activity traits in cattle. (SE = standard error of heritability estimate)

Future breeding programs with activity and genomic data

The integration of real-time data holds great promise for enhancing the accuracy and scope of selection in dairy cattle breeding. One clear advantage is the ability to capture traits that were previously unmeasured or to measure known traits with much higher frequency and precision. By continuously monitoring animals, breeders can obtain a far more detailed picture of each animal's phenotype, sometimes called a "phenomic profile" or digital fingerprint (Neethirajan and Kemp, 2021). This can improve selection in several ways. First, it can increase selection accuracy for existing traits. For example, instead of relying on a single 305-day milk yield, a model could use daily yield curves or deviations as indicators of health and efficiency. High-frequency data tend to reduce noise through averaging or enable detection of anomalies (like drops due to illness), leading to more precise estimates of an animal's true genetic merit for production or health. Second, real-time data enable selection for new traits related to animal resilience, efficiency, and welfare. Breeding programs could rank animals not just for how much milk they produce, but how they produce it, for instance, cows that maintain steady feed intake and milk output even during heat stress or after a social regrouping (indicator of resilience). Continuous monitoring makes it possible to quantify such resilience traits: one could measure how quickly a cow's rumination drops and recovers around a calving event or during a heatwave, and treat the recovery rate as a heritable trait. Similarly, detailed behavioral data can define temperament or welfare traits. Instead of simple chute score temperament assessments, one could use sensor data to derive a "calmness index" based on how a cow's

heart rate or movement spikes in response to handling. These nuanced traits could then be included in breeding objectives to improve robustness and welfare. Researchers are already exploring genetic parameters for traits like feeding behavior, activity levels, and milking behavior that come from automated systems, as a precursor to including them in evaluations (Behren et al., 2023). The continuous nature of sensor data also allows early-life phenotyping of young animals, which can aid selection. For instance, in heifer calves, we could track activity and growth with sensors to identify those with superior efficiency or healthier behavior patterns before they even enter the milking herd, and use that information in selection or culling decisions. Overall, future breeding programs that harness real-time data can shift from improving solely output traits (milk, meat) to improving process and fitness traits (how the animal achieves that output), and ultimately breeding cattle that are not only productive but also healthy, behaviorally well-adjusted, and environmentally resilient. A crucial step toward this future is determining the genetic parameters (heritability, genetic correlations) of novel sensor-derived traits. Early studies in this area are promising, indicating that many behavior and physiological metrics do have a genetic basis (Table 1). Genetic analysis of Brown Swiss dairy cows reported heritabilities of ~0.38 for general temperament and ~0.12 for aggression toward herdmates (Kramer et al., 2013). Those values suggest that selection could alter these behaviors over generations. Similarly, data from automatic milking systems (AMS) has revealed moderate heritabilities for milking behavior traits. Traits like milking speed, refusals, or the time taken for a cow to attach to the milking unit show heritabilities on the order of 0.2–0.5 in various studies (Behren et al., 2023). One study found that the time a cow spends in the milking stall getting the milking unit attached (an indicator of cooperation with the robot) had a heritability ~0.26 (Piwcynski et al., 2021). This indicates substantial genetic variation in how cows behave in robotic milking setups. Genetic correlations from those studies also seem promising, for instance, calmer cows that don't kick off the milking unit tend to have higher milking efficiency (genetic correlation around –0.5 between kicking behavior and milk yield per robot visit) (Behren et al., 2023). This means selecting for good robot behavior could indirectly improve production efficiency. Feeding behavior traits measured by sensors show moderate genetic variation as well. In beef cattle, using electronic feeders, researchers have documented heritabilities of ~0.28 for daily feeding duration and ~0.38 for daily feeding frequency (Brito et al., 2020). These are comparable to heritabilities of traditional growth traits, implying that if feed intake data are collected, one can select for more feed-efficient feeding patterns. Traditional feed efficiency (residual feed intake) is expensive to measure, but with automated systems the industry can gather large-scale data and exploit those moderate heritabilities to breed more feed-efficient animals. Another novel phenotype is health-related sensor traits; for example, automated milking systems can measure electrical conductivity of milk (for mastitis detection) or body weight daily. The heritability of changes in milk conductivity as an indicator of mastitis has been reported in range of 0.23 – 0.53 (Santos et al., 2018; Wethal et al., 2020), therefore, this trait can be managed with genomic selection if the trait is economically important. From the physiological perspective, traits like body temperature or respiration rate measured by sensors tend to have low heritability on the observed scale as one study found a heritability of 0.04 for respiration rate in heat-stressed cows (Luo et al., 2022). This low value suggests that while genetics plays a role, these values are heavily influenced by environment and short-term factors. Nonetheless, even lowly heritable traits might be useful as part of an index if they correlate genetically with important outcomes (for instance, a cow's ability to keep a lower respiration rate under heat stress might genetically correlate with heat tolerance in milk production). As more data accumulates, we expect more reliable estimates of heritability for traits like daily activity level, lying time, rumination time, or vocalization rate. Many of these are likely polygenic, but with enough data and genomic tools, breeding values can be predicted.

The emerging consensus is that most sensor-derived behavioral and welfare traits are at least slightly heritable and thus selective breeding can improve them (Kaur et al., 2023).

Conclusion

The future prospects of digital phenotyping in cattle breeding are extremely promising. We are moving towards an era where an animal's genetic merit may be informed by thousands of data points capturing its behaviour, physiology, and performance under various conditions, marking a significant departure from the sparse and static records of the past. Such "deep phenotyping", when combined with genomic information, can substantially increase the accuracy of selection and enable genetic progress in traits that were previously elusive. This will contribute to breeding cattle that are not just high-producing, but also healthier and more sustainable. The new approach is creating a precision breeding program that mirrors precision farming: making finely tuned decisions for each breeding animal based on rich, real-time data. To reach this goal, ongoing research and development are needed. Key areas for advancement include improving sensor hardware, developing better algorithms to translate raw sensor data into standardized traits, and updating genetic evaluation models to handle new data types.

Acknowledgement

This research was funded by European Union – NextGenerationEU within the project "NEXT GENERATION ANIMAL PRODUCTION" (grant number NPOO.C3.2.R3-I1.04.0141)

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