

The Cow as a Readable System

A guided tour through Runa — one dairy cow, fully instrumented. What we actually know how to read, and where the model breaks down.

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Her name is Runa. She weighs 612 kilograms, produces 28 litres of milk per day, and has never sent an email. She does not have a user interface. But she has a body — and her body, right now, is one of the most densely monitored biological systems on a working farm.

This is not a piece about surveillance. It is not a piece about whether cows should have data rights, or whether precision agriculture is good or bad for animal welfare. Those are real debates. This is something simpler: a guided tour through what we actually know how to read, and what we still cannot.

Start with what is visible.

Runa has a coat. It lies flat in summer and puffs in cold weather. A healthy coat is smooth, uniform, and reflects light cleanly. A rough, dull coat — what farmers call a "staring coat" — can indicate nutritional deficiency, parasites, or systemic illness. This is not a sensor. It is a pattern, and a human eye can read it in under two seconds.

But a camera can too. Modern computer vision systems trained on cattle imagery can detect coat condition changes before a human handler would notice — not because they are smarter, but because they do not blink, do not have bad days, and watch continuously.

Runa also has a body condition score. On a 1–5 scale, it measures fat reserves at specific anatomical landmarks — the loin, the tailhead, the ribs. A score of 3.0 is ideal for a lactating Holstein. Below 2.5 signals that she is burning muscle. Above 3.5 means she was overfed in the dry period and is at risk for metabolic disease. This score is typically assessed by hand — a technician presses their palm into the tailhead and the short ribs, feeling for fat deposits. It takes training. It takes time.

It can also be done with a 3D camera. [1]

From the coat, move to the way she moves.

Runa walks several kilometres a day — between the cubicle barn, the feeding area, the milking parlour. Lameness is one of the most costly diseases in dairy cattle, ranking alongside mastitis and reproductive failure as a driver of production loss, welfare problems, and early culling. [2] A lame cow eats less, produces less milk, conceives less reliably, and is at significantly higher risk of leaving the herd before her productive life is over.

Lameness scoring is traditionally done by eye. A trained observer watches a cow walk and assigns a score from 1 to 5. The challenge is consistency: studies measuring inter-observer agreement on locomotion scoring in commercial herds have found weighted kappa values averaging around 0.5 — well below what would be required for reliable clinical decision-making. [3] Pressure mats, accelerometers on leg bands, and RGB-D cameras — cameras that capture both colour and depth simultaneously — can now detect asymmetric weight distribution, shortened stride length, and altered back posture with a consistency a human observer cannot sustain across a full herd, across a full day. [2][4] These systems do not replace the veterinary examination. But they flag the cow that needs one.

Runa also lies down. She should lie down for 10–14 hours per day. A cow lying less than 8 hours has likely been displaced from her cubicle, is in pain, or is overheated. Her leg-mounted accelerometer records lying bouts, standing bouts, step count, and — in systems with a neck band — an estimate of rumination time based on jaw movement patterns.

Inside Runa's ear is a small transponder. It transmits her identity every time she passes an antenna. The milking robot knows who she is before she enters. The feed station knows her name. The gate after milking can sort her left or right based on a flag in the system. This is the baseline. Everything else is layered on top.

Some farms use boluses — devices swallowed by the cow and lodged in the reticulum, where they sit permanently. A modern bolus measures core body temperature, pH, and in some cases activity. A temperature spike of 0.5°C above baseline, maintained for more than 12 hours, is a strong predictor of infection. A pH drop in the reticulum indicates sub-acute ruminal acidosis — a condition caused by too much fermentable carbohydrate and too little effective fibre.

Mastitis — infection of the udder — is detected at the milking robot through a combination of signals: electrical conductivity of milk, which rises with inflammation; milk yield deviation from the cow's rolling average; and in more sophisticated systems, inline somatic cell count. A single inflamed quarter produces milk that looks slightly different, flows differently, and conducts electricity differently. The robot flags the quarter. The farmer decides.

From the robot, milk goes into the inline analyser — and here the data deepens considerably.

Milk is not uniform. What Runa produces at 6 AM on day 45 of lactation is not what she produces at 6 PM on day 200. Fat percentage, protein percentage, lactose, somatic cell count, urea nitrogen — all of this is readable at the milking point.

Milk urea nitrogen is a proxy for protein metabolism. If the diet has too much degradable protein relative to available energy, urea nitrogen rises. If the diet is energy-deficient, the cow catabolises muscle — and urea nitrogen also rises. The value sits at an intersection of nutrition, metabolism, and reproductive efficiency, and an elevated level is associated with impaired conception rates. [5]

The fat-to-protein ratio tells a parallel story. A ratio above 1.5 in early lactation is a classic indicator of negative energy balance: the cow is producing fat-rich milk because she is mobilising body reserves faster than she is consuming feed. [6] Metabolic stress, made legible in a 10ml sample.

Runa also has a genotype. It was recorded when she was a calf — a small tissue sample from the ear tag, sent to a lab, processed through a 50,000-SNP array, and returned as a genomic estimated breeding value. That value predicts, with some accuracy, her production potential, her health susceptibility, her fertility, and — increasingly — her methane output. [7]

Genome-wide association studies have identified genetic variants in dairy cattle that explain a small but real proportion of the variance in enteric methane production. [7] This is not yet used routinely at farm level, but the direction is clear: future selection indices will incorporate methane efficiency alongside milk litres and somatic cell score. Runa cannot choose her genome. But her genome shapes how efficiently she converts feed to milk, and how much gas she exhales per kilogram of product.

The rumen is where most of that gas comes from.

It is a fermentation chamber holding 80–100 litres of partially digested feed, microorganisms, and gas. Without the rumen microbiome — the bacteria, fungi, protozoa, and viruses that live there — Runa cannot digest fibre at all. She would starve on grass.

The rumen virome is still largely unmapped. A 2012 metagenomic study identified thousands of viral sequences in cattle rumen samples, the majority with no known homologs in any database. [8] This is not an exotic edge case. It means the core of the digestive system that supports all of European dairying contains vast biological machinery we have not yet named.

The protozoa are better understood. Rumen ciliates — organisms large enough to see under a light microscope — are active predators inside the rumen, consuming bacteria and contributing to the rumen's hydrogen balance. [9] Some ciliate species are closely associated with methanogenic archaea, forming physical consortia that may directly influence how much methane the rumen produces.

Only around 3% of a cow's enteric methane exits as flatus. The rest — roughly 97% — leaves through the mouth and nostrils, primarily through eructation. [10] A high-starch diet produces less methane per unit of feed than a high-fibre diet, but the relationship is not simple. It depends on the rumen microbiome's composition, the ratio of acetate to propionate in volatile fatty acid production, and the availability of alternative hydrogen sinks. The rumen is a system within the system.

Measuring Runa's methane output at the individual level is technically difficult. The gold standard — respiration chambers, where the cow spends 48–72 hours in a sealed room with atmospheric sensors — is expensive, stressful for the animal, and impractical at scale.

Alternatives include SF₆ tracer gas and GreenFeed machines that measure methane concentration in the cow's breathing zone as she feeds. A more recent approach places a sensor directly inside the rumen. A proof-of-concept published in 2016 demonstrated a swallowable intra-ruminal capsule with infrared gas sensors lodged in the reticulum, measuring CH₄ and CO₂ continuously in live cattle and validating readings against respiration chamber data. [11] It captures the internal signal rather than the exhaled signal — continuously, without requiring the animal to present herself at a measurement station. The trade-off is that converting rumen gas concentration into total emission flux requires a model. That model introduces its own uncertainty.

Not all farms use all of this. A large commercial dairy will typically have ear tag transponders, a milking robot with inline milk analysis, and leg accelerometers — these are now standard. Neck band rumination sensors are common. Body condition scoring cameras are beginning to appear. Genomic testing of replacement heifers is routine in breeding herds. Bolus sensors for pH and temperature are specialist. Individual methane sensing is research and pilot farms only.

The sensors lower on that list are not obscure. They are published, validated, and commercially available. They are just not yet economically routine. The direction of travel is clear.

Above the cubicle rows, a single RGB-D camera can monitor every cow in its field of view, continuously, without physical contact. Systems currently deployed or in late-stage trials can automatically score body condition, detect lameness, track individual animals by coat pattern without ear tags, count lying and standing periods, and identify social interactions — crowding at the feed fence, displacement from cubicles. [1][4][12]

This changes the unit of analysis from the individual sensor reading to the population-level pattern. It makes visible what is invisible when you are looking at one cow at a time: that three cows in cubicle row B are standing unusually, or that the average lying time across the herd dropped 90 minutes in the week following a group expansion. This is surveillance, in the literal sense. Whether it constitutes welfare improvement or welfare monitoring-as-performance depends entirely on what the farmer does with the information.

Which brings the problem into focus.

Sensors produce data. Data produces alerts. Alerts produce decisions — or they produce alert fatigue. One of the consistent findings in precision livestock farming research is that alert uptake rates drop sharply when false positive rates are high. A study tracking mastitis alerts from an automatic milking system over two years found that out of more than 11,000 alerts, fewer than 2% were true positives. [13] At that point, the system has not improved welfare. It has provided the appearance of monitoring.

Runa's value to the system is that she is consistent. Her individual baseline — her typical daily milk yield, her typical lying time, her typical step count — is the reference against which deviations are measured. An alert that says "this cow's milk yield is 4 kilograms below her 14-day rolling average" is more useful than one that says "this cow's yield is below breed average." The latter compares her to a population. The former compares her to herself.

Individualised baselines require longitudinal data. The system needs to have been watching Runa long enough to know what Runa-normal looks like. This is the underacknowledged requirement of precision livestock farming: it takes time. A newly installed sensor stack is not yet doing what it will eventually be able to do.

Runa does not ask for anything. She has no goal state she can articulate.

But her body has needs — and those needs, when unmet, produce signals. She stands longer when her cubicles are uncomfortable. She eats less when she is in pain. Her milk production drops when her energy balance is negative. Her rumen pH falls when her diet shifts too fast. These are not requests. They are outputs

of a biological system under load.

The premise of precision livestock farming is that these outputs can be read reliably enough to inform intervention — that you can catch the problem before it becomes a welfare crisis, a production loss, or a treatment cost.

The honest answer, looking at the evidence, is: sometimes. Some signals are robust, well-validated, and actionable. Others are noisy, contextually dependent, or only meaningful in combination with data from other layers. Runa is not a dashboard. She is an animal that a dashboard is attempting to model.

The model is incomplete. The model is also, increasingly, the best we have.

The most important variable in Runa's welfare is not the sensor. It is whether the person looking at the screen knows what to do with what they see.

Precision livestock farming does not replace stockmanship. At its best, it extends it — giving the skilled farmer a finer-grained picture of what is happening to animals she cannot observe continuously. At its worst, it creates the illusion of monitoring without the reality of care.

Runa will not know the difference.

But the data will.

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Correction note

This article was updated on 2026-05-06. The following corrections were made to the original version published on 2026-05-05:

Four citations were replaced after post-publication source verification. The original reference for lameness costs (Norrington & Valros 2014) was replaced with the primary economic study by Kossaihati & Esslemont (1997). The original reference for inter-observer lameness scoring agreement was replaced with the primary measurement study by Thomsen et al. (2008). A dedicated citation for RGB-D lameness detection (Viazzi et al. 2014) was added; the previous citation covered body condition scoring only. The eructation figure was updated from a 1976 sheep study to primary data on dairy cows (Muñoz et al. 2012). One citation for intra-ruminal gas sensing could not be verified and was replaced with Bishop-Hurley et al. (2016), which describes the same technology.

The core claims of the article are unchanged. The corrections affect source quality and precision, not the conclusions drawn from the evidence.

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