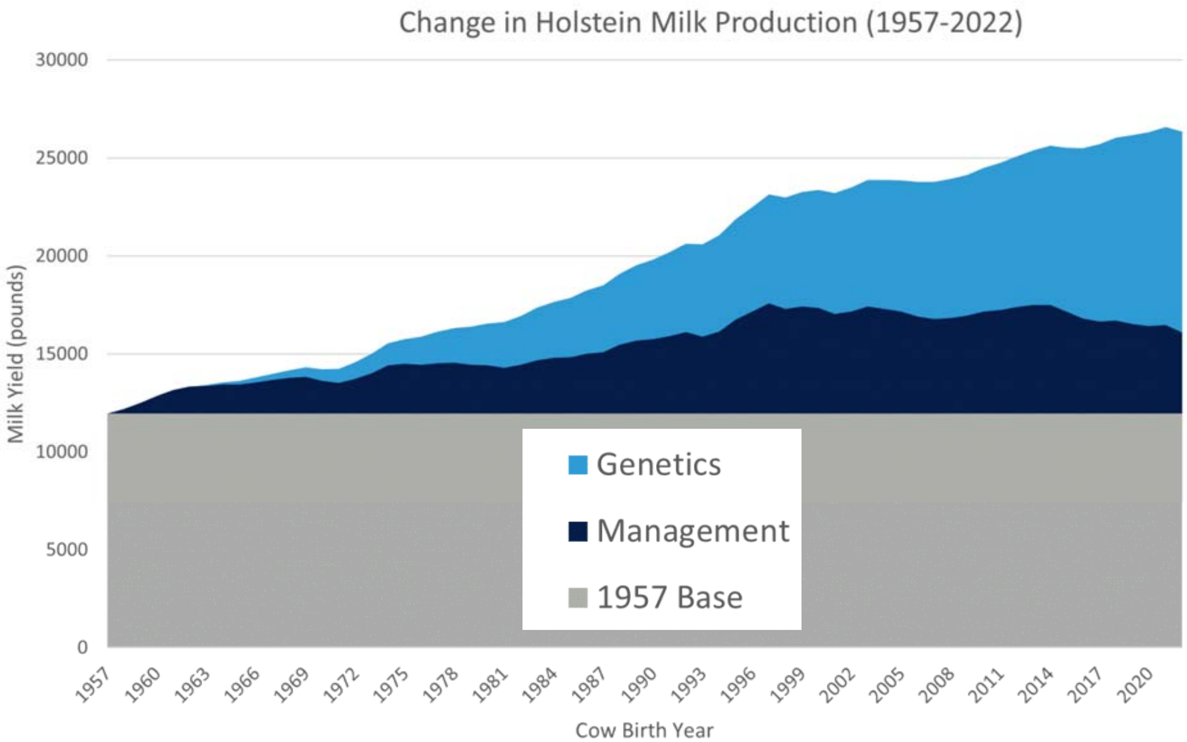
Using data from sensors and other technologies to enhance dairy cattle breeding programs

By Luiz Brito

PURDUE UNIVERSITY

The Role of Genetics in Dairy Production



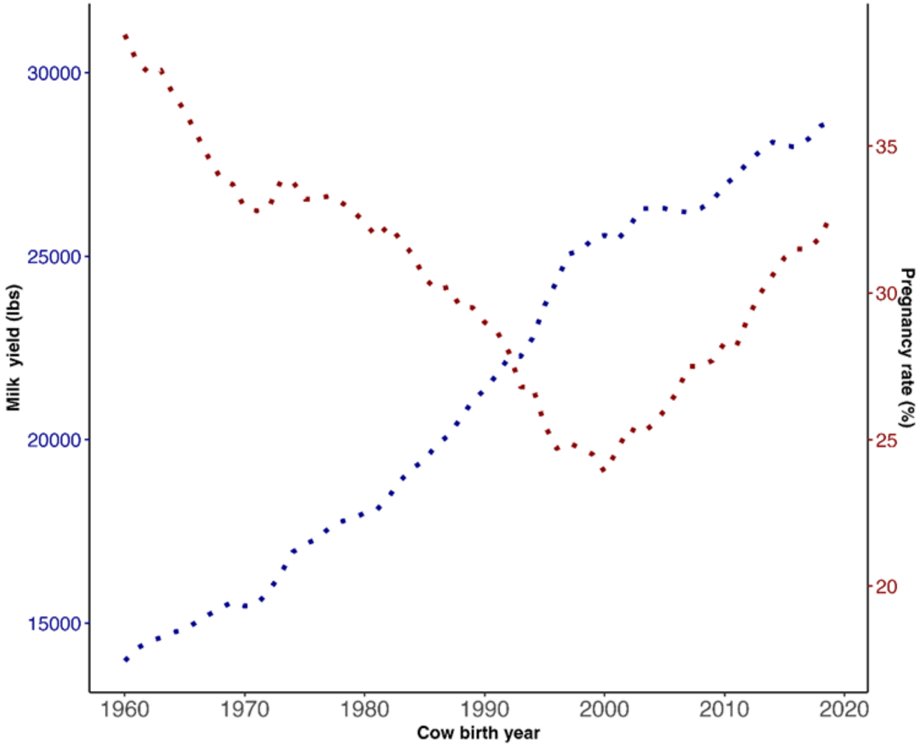
Source: CDCB, 2025 (https://uscdcb.com/impact/)

- ✓ **More milk with fewer cows: > efficiency**
- ✓ **Permanent and cumulative improvements**
- ✓ **Better management and environmental conditions needed for full expression of genetic merit**

ICAR THE GLOBAL STANDARD FOR LIVESTOCK DATA

FIL IDF Fédération Internationale du Lait • International Dairy Federation

(Undesirable) Correlated Responses



Source: CDCB, 2025 (https://uscdcb.com/impact/)

Indexes

Genetic tools have reversed cow fertility decline

Kristen Parker Gaddis April 25, 2023

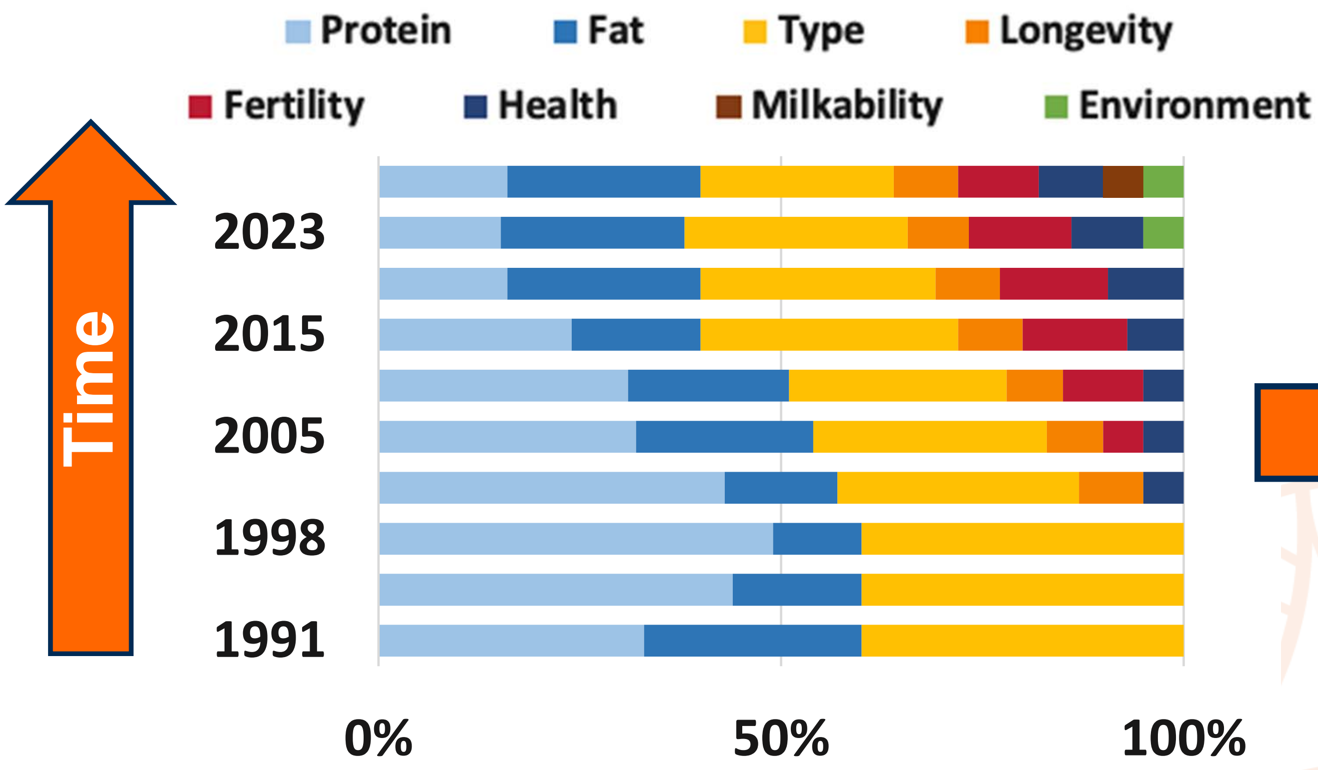
A myth in U.S. Holstein breeding is the continued decrease in dairy cow fertility as milk production has increased. What is the status on this statement today?

It is true that U.S. Holsteins experienced a decline in fertility until 2000 during decades of tremendous production gains. It is also true that production and fertility are negatively correlated in farm animals. Said another way, higher-producing cows are genetically predisposed for decreased reproductive efficiency.

Kristen Gaddis
Geneticist / Council on Dairy Cattle Breeding
Email Kristen Gaddis

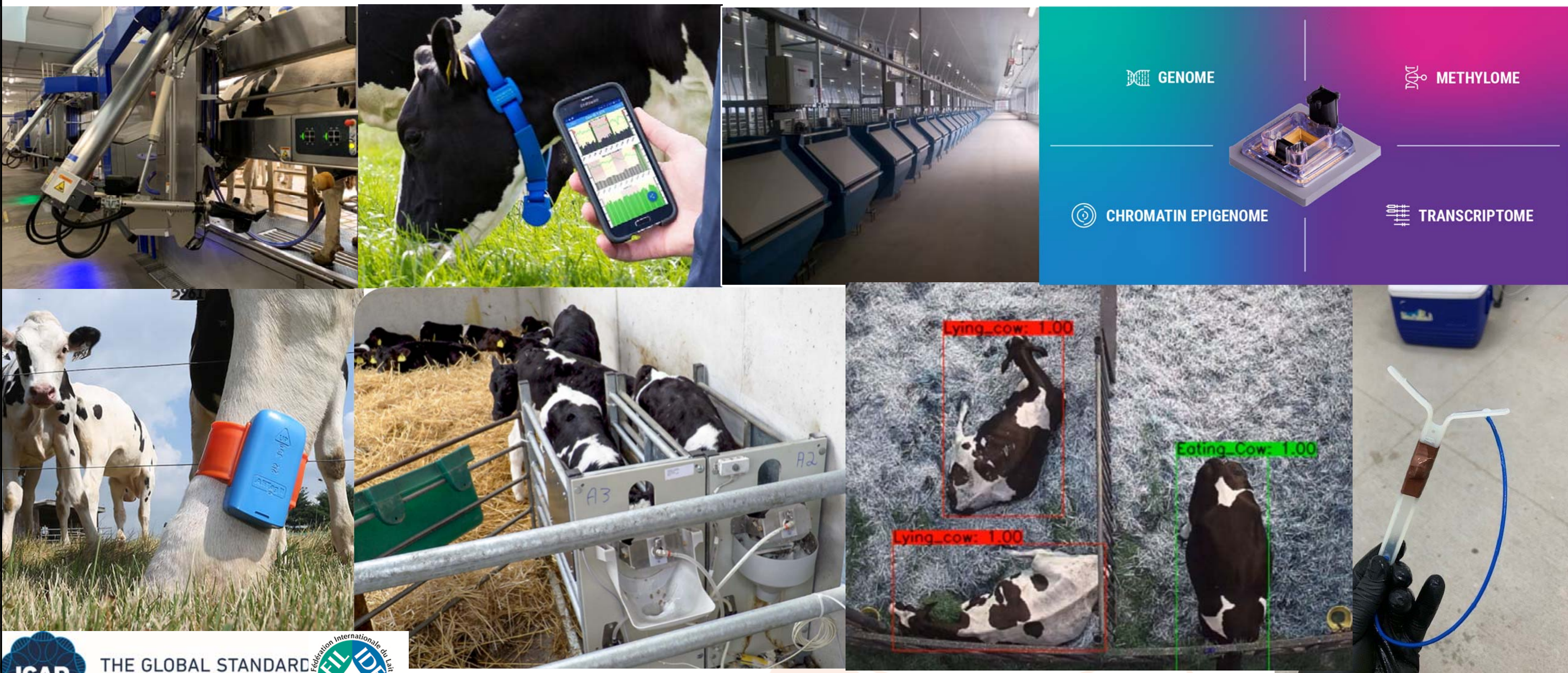
What is happening with traits that are not currently being measured?

More Balanced (Sustainable) Breeding Goals



Source: Miglior *et al.* (2025)

Sensors and Other Technologies



Sensors and Other Technologies

- ✓ **Improve the quality of life of dairy farmers** (Tse *et al.*, 2017; Hogan *et al.*, 2022)
- ✓ **Enhance labor output and labor cost over time** (Liu et al., 2023)
- ✓ **Increase reproduction efficiency and on-farm management** (Reith and Hoy, 2018)
- ✓ **Contribute to improving animal health, welfare, and productive efficiency** (Dawkins, 2021; Simitzis *et al.*, 2021)
- ✓ **Generate high-frequency, objective, and large-scale phenotypes, which are essential for breeding purposes** (Brito *et al.*, 2020; 2025)

Challenges More Related to Breeding Purposes

- PLF **market fragmentation and inconsistency**: multiple devices and brands with different algorithms for the same trait (e.g., activity, rumination): inconsistent outcomes
- **Limited robustness of sensors**: they may perform differently depending on life stage, physiological status, farm system, or environmental conditions
- Lack of transparency, supporting information, and metadata: **insufficient background information** on data generation procedures (e.g., variable definitions, units, resolution, and frequency of records) and software/algorithm updates
- **Heterogeneous recording**: data may be provided at different resolutions (e.g., hourly vs. daily summaries; average versus sum)

ICAR-IDF Sensor Initiative

Network. Guidelines. Certification.

ICAR IDF initiative on sensor data for functional traits: Genetics and reference standards for rumination

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ICAR Functional Traits Working Group, IDF Standing Committee of Animal Health and Welfare, international experts, manufacturers

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***Invited review:* Using data from sensors and other precision farming technologies to enhance the sustainability of dairy cattle breeding programs**

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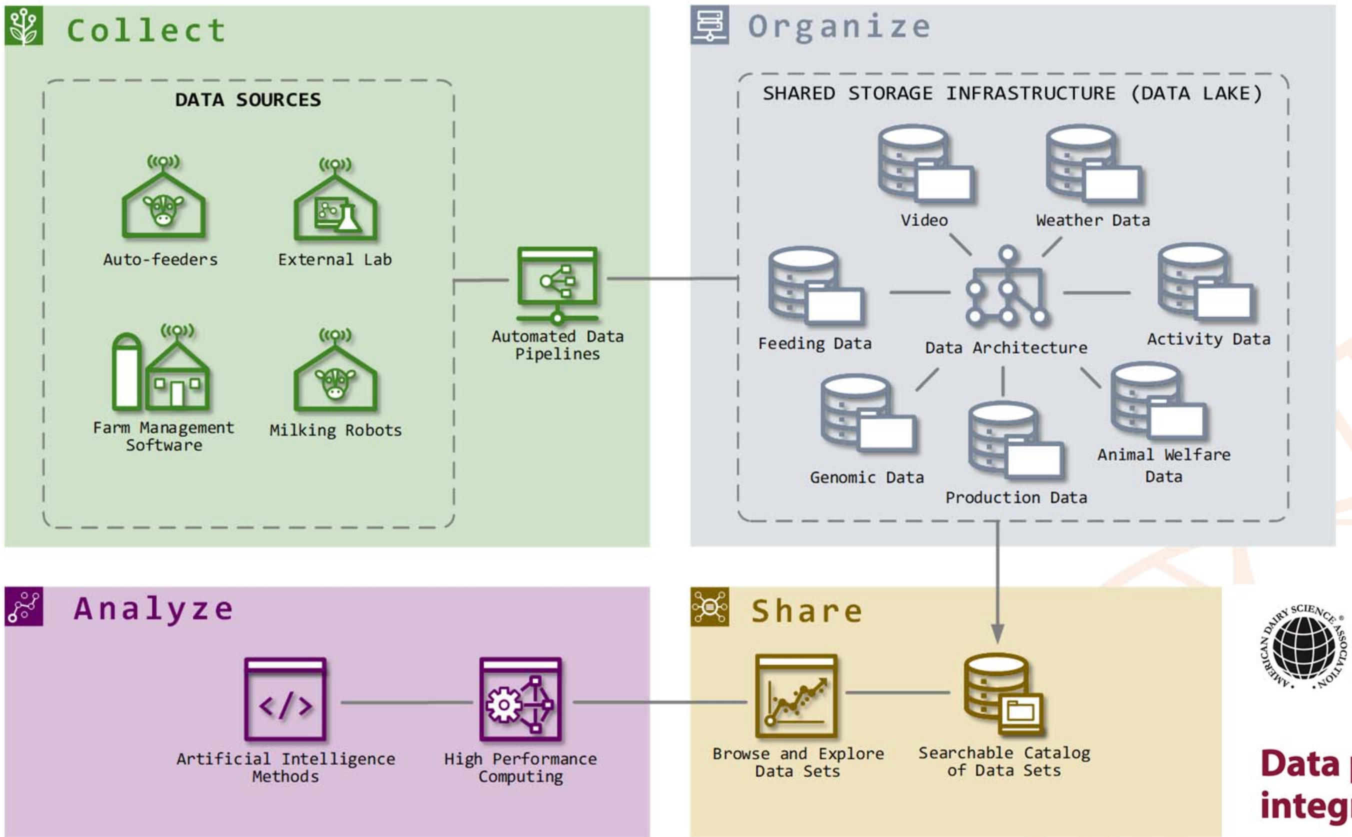
Data Integration

- ✓ Most data remain farm-specific "silos" and are **underutilized in genetic evaluations**
- ✓ Collaborations between farmers, DHIA, breeding organizations, and manufactures ➔ establishment of **data exchange pipelines**
- ✓ **Examples of data integration initiatives**: PASDE (Purdue Univ.; Boerman *et al.,* 2025), DairyBrain (Cabrera *et al.,* 2020), D4Dairy (Egger-Danner *et al.,* 2022), Nordic Cattle Database, Gigacow (Klingström *et al.,* 2022), International Dairy Data Exchange Network (IDDEN), and other companies (e.g., Iyotah, Vyla, Dairy Data Warehouse, Join-Data, Dairy Performance Network, AgriGates, Connecterra, etc.)

Purdue Animal Sciences Research Data Ecosystem (PASDE)



Ag Data Services

College of Agriculture

JDS Communications®
TBC; TBC

https://doi.org/10.3168/jdsc.2024-0723
Technical Note
Animal Nutrition and Farm Systems

Data processing techniques to improve data integration from dairy farms

Jacquelyn P. Boerman,[1]* Luiz F. Brito,[1]* Maria E. Montes,[1] Jacob M. Maskal,[1] Jarrod Doucette,[2] and Kirby Kalbaugh[2]

ICAR THE GLOBAL STANDARD FOR LIVESTOCK DATA

Data Cleaning and Quality Assurance

✓ Essential for accuracy, reliability, and comparability of phenotypes

✓ Schodl *et al.* (2024) proposed a 5-step framework:

- **Validate the data merging process** (e.g., non-unique device IDs, animal ID–device alignment, time zones)
- **Understand the data** (e.g., type/units, raw vs. processed, **comprehensive data visualization**)
- **Check data completeness**: define strategies to handle missing and duplicate records
- **Address technology-related noise** (e.g., calibration issues, software updates)
- **Detect outliers and verify plausibility** (biological ranges, ±3 SD)

Sensor data cleaning for applications in dairy herd management and breeding

Katharina Schodl[1*], Anna Stygar[2], Franz Steininger[1] and Christa Egger-Danner[1] on behalf of the D4Dairy-Consortium

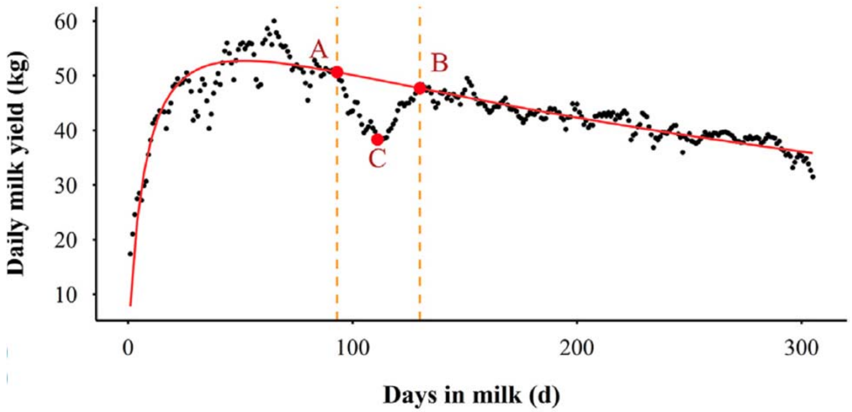
Deriving Novel Traits: Some Key Points

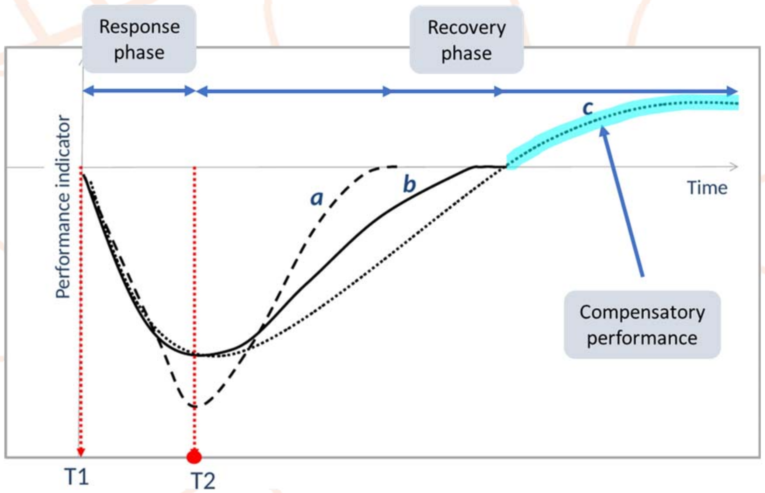
- ✓ **Criteria for inclusion in breeding programs**: heritable and repeatable; capture biological relevance or be genetically correlated with breeding goal traits; routinely measured, standardized, and available at large-scale and low cost
- ✓ Detailed **documentation and metadata** on the recording methods and variables of interest
- ✓ Proper data merging/integration, editing, and quality assurance
- ✓ Extra care needed when merging **"similar" variables** from different sensors: check ranges, mean, and variance; genetic correlation between variables, animal re-ranking, etc.
- ✓ Statistical model development also requires data from potential systematic/fixed effects
- ✓ Genetic and genomic analyses of derived traits (as usual)

Great Opportunity for Breeding More Resilient Animals

- ✓ **Resilience:** "individual capacity to be **minimally affected by environmental disturbances** or to **rapidly bounce back** to the previously undisturbed states" (Colditz *et al.*, 2016; Berghof *et al.*, 2019)

- ✓ In terms of **animal welfare**: more resilient animals will have a less negative experience during the environmental disturbance





Source: Taghipoor *et al.* (2023)

Great Opportunity for Breeding More Resilient Animals

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Between-herd variation in resilience and relations to herd performance

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Validation of resilience indicators by estimating genetic correlations among daughter groups and with yield responses to a heat wave and disturbances at herd level

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Genomic-based genetic parameters for resilience across lactations in North American Holstein cattle based on variability in daily milk yield records

Shi-Yi Chen,[1,2] Jacquelyn P. Boerman,[1] Leonardo S. Gloria,[1] Victor B. Pedrosa,[1] Jarrod Doucette,[3] and Luiz F. Brito[1]*

Genetic parameters for novel climatic resilience indicators derived from automatically-recorded vaginal temperature in lactating sows under heat stress conditions

Hui Wen[1], Jay S. Johnson[2], Leonardo S. Gloria[1], Andre C. Araujo[1], Jacob M. Maskal[1], Sharlene Olivette Hartman[1], Felipe E. de Carvalho[1], Artur Oliveira Rocha[1], Yijian Huang[3], Francesco Tiezzi[4,5], Christian Maltecca[4], Allan P. Schinckel[1] and Luiz F. Brito[1]*

Exploring milk loss and variability during environmental perturbations across lactation stages as resilience indicators in Holstein cattle

Ao Wang[1], Luiz F. Brito[2], Hailiang Zhang[1], Rui Shi[1], Lei Zhu[1], Dengke Liu[3], Gang Guo[4] and Yachun Wang[1]*

Opportunities to Improve Resilience in Animal Breeding Programs

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Wageningen University & Research Animal Breeding and Genomics, Wageningen, Netherlands

Investigating the relationship between fluctuations in daily milk yield as resilience indicators and health traits in Holstein cattle

Ao Wang,[1] Guosheng Su,[2] Luiz F. Brito,[3] Hailiang Zhang,[1] Rui Shi,[1] Dengke Liu,[4] Gang Guo,[5] and Yachun Wang[1]*

Genetic analysis of resilience indicators based on milk yield records in different lactations and at different lactation stages

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Exploring Phenotypes for Disease Resilience in Pigs Using Complete Blood Count Data From a Natural Disease Challenge Model

Xuechun Bai[1], Austin M. Putz[2], Zhiquan Wang[1], Frédéric Fortin[3], John C. S. Harding[4], Michael K. Dyck[1], Jack C. M. Dekkers[2], Catherine J. Field[1], Graham S. Plastow[1] and PigGen Canada†*

Sensor-based Health Traits

Table 1. Heritability estimates for automatically recorded indicators of health in dairy cattle populations[1]

Trait	Sensor Type	N	Breed	$h^2 \pm SE$	Reference
EC	AMS integrated sensor	1,714	Holstein	0.22 ± 0.04	Dechow et al. (2020)
Daily average EC	AMS integrated sensor	8,455	Holstein	0.48 ± 0.10	Lu et al. (2024)
EC at milking session 1	AMS integrated sensor	8,455	Holstein	0.46 ± 0.10	Lu et al. (2024)
EC at milking session 2	AMS integrated sensor	8,455	Holstein	0.47 ± 0.10	Lu et al. (2024)
EC at milking session 3	AMS integrated sensor	8,455	Holstein	0.47 ± 0.10	Lu et al. (2024)
EC	AMS integrated sensor	4,280	Holstein	0.46 ± 0.02	Medeiros et al. (2024)
EC	AMS integrated sensor	4,507	Holstein	0.38 to 0.49	Pedrosa et al. (2023)
EC	AMS integrated sensor	1,899	Holstein	0.38 ± 0.01	Piwczyński et al. (2021)
EC, front left	AMS integrated sensor	922	Holstein	0.46 ± 0.09	Santos et al. (2018)
EC,front right	AMS integrated sensor	922	Holstein	0.44 ± 0.09	Santos et al. (2018)
EC, rear left	AMS integrated sensor	922	Holstein	0.37 ± 0.08	Santos et al. (2018)
EC, rear right	AMS integrated sensor	922	Holstein	0.38 ± 0.09	Santos et al. (2018)
Overall EC	AMS integrated sensor	922	Holstein	0.53 ± 0.09	Santos et al. (2018)
EC	AMS integrated sensor	1,486	Holstein	0.36 ± 0.04	Sitkowska et al. (2024)
EC, mean	AMS integrated sensor	4,714	Norwegian Red	0.35 ± 0.03	Wethal et al. (2020)
EC, maximum	AMS integrated sensor	4,714	Norwegian Red	0.23 ± 0.02	Wethal et al. (2020)
Blood in milk	AMS integrated sensor	1,714	Holstein	0.09 ± 0.03	Dechow et al. (2020)
Smoothed milk BHB values (ket_s1)	Herd Navigator (BHB)	794	Nordic Red	0.09 ± 0.07	Häggman et al. (2019)
Smoothed milk BHB values (ket_s2)	Herd Navigator (BHB)	794	Nordic Red	0.07 ± 0.07	Häggman et al. (2019)
Milk temperature	AMS integrated sensor	1,899	Holstein	0.41 ± 0.01	Piwczyński et al. (2021)
SCS	AMS integrated sensor	1,899	Holstein	0.36 ± 0.01	Piwczyński et al. (2021)
Mastitis susceptibility	AMS integrated sensor	1,791	Holstein	0.07 ± 0.03	Welderufael et al. (2017)
Mastitis recovery	AMS integrated sensor	1,791	Holstein	0.08 ± 0.03	Welderufael et al. (2017)
Log-transformed online cell count	AMS integrated sensor	1,490	Norwegian Red	0.09 ± 0.03	Wethal et al. (2020)

[1]AMS = automated milking system; EC = electrical conductivity.

All tables included in Brito *et al.* (2025):
https://doi.org/10.3168/jds.2025-26554

Sensor-based Behavioral Traits

Table 2. Heritability (h^2) estimates for cow behavioral traits derived from automated milking systems (milking robots)

Trait	N	Breed	$h^2 \pm$ SE	Reference
Choice consistency score (5–50 DIM, primiparous)	730	Holstein	0.04 ± 0.06	Løvendahl et al. (2016b)
Choice consistency score (5–50 DIM, multiparous)	1,231	Holstein	0.05 ± 0.04	Løvendahl et al. (2016b)
Choice consistency score (51–110 DIM, primiparous)	730	Holstein	0.11 ± 0.08	Løvendahl et al. (2016b)
Choice consistency score (51–110 DIM, multiparous)	1,231	Holstein	0.07 ± 0.05	Løvendahl et al. (2016b)
Choice consistency score (111–215 DIM, primiparous)	730	Holstein	0.14 ± 0.08	Løvendahl et al. (2016b)
Choice consistency score (111–215 DIM, multiparous)	1,231	Holstein	0.07 ± 0.04	Løvendahl et al. (2016b)
Choice consistency score (216–305 DIM, primiparous)	730	Holstein	0.08 ± 0.07	Løvendahl et al. (2016b)
Choice consistency score (216–305 DIM, multiparous)	1,231	Holstein	0.02 ± 0.03	Løvendahl et al. (2016b)
Knock off (binary)	922	Holstein	0.03 ± 0.03	Santos et al. (2018)
Log-transformed handling time	4,883	Norwegian Red	0.07 ± 0.02	Wethal and Heringstad (2019)
Number of kick-offs	4,883	Norwegian Red	0.06 ± 0.01	Wethal and Heringstad (2019)
Number of kick-offs	1,714	Holstein	0.08 ± 0.02	Dechow et al. (2020)
Proportion of milkings with kick-offs	4,883	Norwegian Red	0.13 ± 0.03	Wethal and Heringstad (2019)
Preference consistency score	4,249	Holstein	0.09 ± 0.01	Berat et al. (2025)
Preference consistency score	2,258	Holstein	0.07 ± 0.02	Løvendahl and Buitenhuis (2022)
Preference consistency score	2,407	Jersey	0.13 ± 0.03	Løvendahl and Buitenhuis (2022)
Temperament	72,683	Norwegian Red	0.05 ± 0.01	Wethal et al. (2020)
Time profile (profile of the diurnal milking time)	2,258	Holstein	0.11 ± 0.02	Løvendahl and Buitenhuis (2022)
Time profile (profile of the diurnal milking time)	2,407	Jersey	0.04 ± 0.02	Løvendahl and Buitenhuis (2022)

THE GLOBAL STANDARD FOR LIVESTOCK DATA

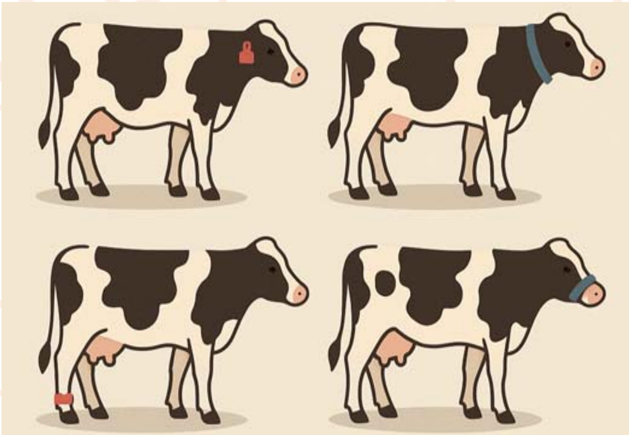
All tables included in Brito *et al.* (2025): https://doi.org/10.3168/jds.2025-26554

Sensor-based Activity Traits

Table 3. Heritability (h^2) estimates for sensor-based activity traits measured in Holstein dairy cows

Trait	Sensor type or brand	N	$h^2 \pm SE$	Reference
Activity time (min/24 h)	SenseHub (Allflex Livestock Intelligence) collar	453	0.14 ± 0.06	Lemal et al. (2024)
Activity (daily)	Pedometer	635	0.19 ± 0.06	Nascimento et al. (2024)
Activity (weekly)	Pedometer	635	0.23 ± 0.07	Nascimento et al. (2024)
Activity	Electronic activity neck tags (SCR Heatime HR system)	1,171	0.09 ± 0.05	Schöpke and Weigel (2014)
Duration of high activity episode	Electronic activity tags (neckbands)	11,522	0.03 ± 0.01	Ismael et al. (2016)
Eating rate (kg/h)	Automated feeders	842	0.46 ± 0.09	Lin et al. (2013)
Eating time (first parity)	SenseHub dairy sensors (Allflex)	142	0.42 ± 0.09	Atashi et al. (2024)
Eating time (second parity)	SenseHub dairy sensors (Allflex)	243	0.45 ± 0.04	Atashi et al. (2024)
Eating time (first parity)	SenseHub dairy sensor (Allflex)	142	0.42 ± 0.09	Atashi et al. (2024)
Eating time (second parity)	SenseHub dairy sensor (Allflex)	243	0.45 ± 0.04	Atashi et al. (2024)
Eating time (min/24 h)	SenseHub (Allflex) collar	453	0.12 ± 0.05	Lemal et al. (2024)
Interval from calving to first high activity	Electronic activity tags fitted on neckbands	11,522	0.11 ± 0.02	Ismael et al. (2016)
Lying time (daily)	SMARTBOW ear-tag accelerometer	728	0.37 ± 0.07	Nascimento et al. (2024)
Lying time (weekly)	SMARTBOW ear-tag accelerometer	728	0.48 ± 0.09	Nascimento et al. (2024)
Strength of high activity episode	Electronic activity tags (neckbands)	11,522	0.03	Ismael et al. (2016)
Daily sum activity (DIM 7 and 14)	Lely	1,084	0.13 ± 0.09	Schodl et al. (2024)
Daily SD activity (DIM 7 and 14)	Lely	1,084	0.33 ± 0.14	Schodl et al. (2024)
Mean daily activity sum over 5–7 and 12–14 DIM	Lely	1,084	0.24 ± 0.07	Schodl et al. (2024)
Mean daily activity SD over 5–7 and 12–14 DIM	Lely	1,084	0.35 ± 0.09	Schodl et al. (2024)
Regression slope of activity daily sum over 5–7 and 12–14 DIM	Lely	1,084	0.12 ± 0.03	Schodl et al. (2024)
Regression slope of daily SD over 5–7 and 12–14 DIM	Lely	1,084	0.18 ± 0.04	Schodl et al. (2024)
Mean daily activity sum over 150 DIM	Lely	1,084	0.15 ± 0.06	Schodl et al. (2024)
Mean daily activity SD over 150 DIM	Lely	1,084	0.19 ± 0.07	Schodl et al. (2024)
Regression slope of daily activity sum over 150 DIM	Lely	1,084	0.22 ± 0.13	Schodl et al. (2024)
Regression slope of daily activity SD over 150 DIM	Lely	1,084	0.11 ± 0.14	Schodl et al. (2024)
Mean daily activity sum over 305 DIM	Lely	1,084	0.18 ± 0.05	Schodl et al. (2024)
Mean daily activity SD over 305 DIM	Lely	1,084	0.18 ± 0.06	Schodl et al. (2024)
Regression slope of daily activity sum over 305 DIM	Lely	1,084	0.18 ± 0.13	Schodl et al. (2024)
Regression slope of daily activity SD over 305 DIM	Lely	1,084	0.26 ± 0.17	Schodl et al. (2024)
Daily activity sum on 7 and 14 DIM	Smaxtec	409	0.18 ± 0.11	Schodl et al. (2024)
Daily activity SD on 7 and 14 DIM	Smaxtec	409	0.55 ± 0.21	Schodl et al. (2024)
Mean daily activity sum over 5–7 DIM and 12–14 DIM	Smaxtec	409	0.34 ± 0.11	Schodl et al. (2024)
Mean daily activity SD over 5–7 DIM and 12–14 DIM	Smaxtec	409	0.47 ± 0.11	Schodl et al. (2024)
Regression slope of daily activity sum over 5–7 DIM and 12–14 DIM	Smaxtec	409	0.00 ± 0.00	Schodl et al. (2024)
Regression slope of daily activity SD over 5–7 DIM and 12–14 DIM	Smaxtec	409	0.07 ± 0.03	Schodl et al. (2024)
Mean daily activity sum over 150 DIM	Smaxtec	409	0.00 ± 0.00	Schodl et al. (2024)
Mean daily activity SD over 150 DIM	Smaxtec	409	0.00 ± 0.00	Schodl et al. (2024)
Regression slope of daily activity sum over 150 DIM	Smaxtec	409	0.00 ± 0.00	Schodl et al. (2024)
Regression slope of daily activity SD over 150 DIM	Smaxtec	409	0.00 ± 0.00	Schodl et al. (2024)
Mean daily activity sum over 305 DIM	Smaxtec	409	0.00 ± 0.00	Schodl et al. (2024)
Mean daily activity SD over 305 DIM	Smaxtec	409	0.00 ± 0.00	Schodl et al. (2024)
Regression slope of daily activity sum over 305 DIM	Smaxtec	409	0.00 ± 0.00	Schodl et al. (2024)
Regression slope of daily activity SD over 305 DIM	Smaxtec	409	0.00 ± 0.00	Schodl et al. (2024)
Activity: mean, SD, and median on the day of milk recording (test day)	Lely	1,289	0.09–0.16 (±0.01–0.04)	Schodl et al. (2023)
Activity: deviation between mean and SD at test day and 5 and 10 d before	Lely	1,289	0.12–0.19 (±0.01–0.05)	Schodl et al. (2023)
Activity: mean, SD, mean SD and median over 3–305 DIM	Lely	1,289	0.17–0.20 (±0.03)	Schodl et al. (2023)

Large variability on the definitions of activity variables, algorithms used, data editing, sensor attachment place, etc.



All tables included in Brito *et al.* (2025): https://doi.org/10.3168/jds.2025-26554

Rumination Traits

Table 4. Heritability estimates for sensor-based rumination time traits in dairy cattle populations

Trait	Sensor type or brand	N	h² ± SE	Reference
Rumination time (first parity)	SenseHub dairy sensor (Allflex)	142	0.45 ± 0.06	Atashi et al. (2024)
Rumination time (second parity)	SenseHub dairy sensors (Allflex)	243	0.43 ± 0.02	Atashi et al. (2024)
Rumination time (First lactation)	SenseHub dairy sensors (Allflex)	142	0.45 ± 0.06	Atashi et al. (2024)
Rumination time (second parity)	SenseHub dairy sensor (Allflex)	243	0.43 ± 0.02	Atashi et al. (2024)
Rumination time (Early) - research herds	Microphone-based rumination monitoring sensor	159	0.14 ± 0.27	Byskov et al. (2017)
Rumination time (Late) - research herds	Microphone-based rumination monitoring sensor	159	0.23 ± 0.26	Byskov et al. (2017)
Rumination time (Peak) research herds	Microphone-based rumination monitoring sensor	159	0.44 ± 0.34	Byskov et al. (2017)
Rumination time (Total) research herds	Microphone-based rumination monitoring sensor	159	0.33 ± 0.16	Byskov et al. (2017)
Rumination time (Early) - commercial herds	Microphone-based rumination monitoring sensor	10,475	0.29 ± 0.03	Byskov et al. (2017)
Rumination time (Peak) - commercial herds	Microphone-based rumination monitoring sensor	10,475	0.28 ± 0.03	Byskov et al. (2017)
Rumination time (Mid) - commercial herds	Microphone-based rumination monitoring sensor	10,475	0.32 ± 0.04	Byskov et al. (2017)
Rumination time (late) - commercial herds	Microphone-based rumination monitoring sensor	10,475	0.31 ± 0.04	Byskov et al. (2017)
Rumination time (total) - commercial herds	Microphone-based rumination monitoring sensor	10,475	0.30 ± 0.03	Byskov et al. (2017)
Rumination time	Accelerometer-based neck tag (Lely Qwes HR-LDn)	1,486	0.14 ± 0.04	Sitkowska et al. (2024)
Rumination time	SenseHub collar (Allflex)	453	0.19 ± 0.05	Lemal et al. (2024)
Rumination time	Electronic collar with acoustic sensors (Allflex SCR, Hi Tag)	656	0.45 ± 0.14	Lopes et al. (2024)
Rumination time	Collar with tag (Lely Qwes)	775	0.17 ± 0.06	López-Paredes et al. (2020)
Rumination time (Early)	Neck collar with a tag (microphone + three-axis accelerometer)	710	0.32	Moretti et al. (2018)
Rumination time (Mid)	Neck collar with a tag (microphone + three-axis accelerometer)	710	0.34	Moretti et al. (2018)
Rumination time (Late)	Neck collar with a tag (microphone + three-axis accelerometer)	710	0.35	Moretti et al. (2018)
Rumination Time (weekly)	SMARTBOW ear-tag accelerometer	728	0.25 ± 0.08	Nascimento et al. (2024)
Rumination time (daily)	SMARTBOW ear-tag accelerometer	728	0.19 ± 0.06	Nascimento et al. (2024)
Mean, SD and median on the day of milk recording (test day)	Lely	1,289	0.03–0.30 ± 0.01–0.04	Schodl et al. (2023)
Deviation between mean and SD at test day and 5 and 10 d before	Lely	1,289	0.10–0.37 ± 0.01–0.05	Schodl et al. (2023)
Mean, SD, mean SD and median over 3–305 DIM	Lely	1,289	0.39–0.50 ± 0.06	Schodl et al. (2023)
Mean and SD on day of milk recording (test day)	Lely	834	0.06–0.18 ± 0.03–0.04	Schodl et al. (2022)
Deviation between mean and SD at test day and 5 d before	Lely	834	<0.01–0.04 ± 0.01–0.02	Schodl et al. (2022)
Regression slope of daily mean and SD over 5days before to test day	Lely	834	<0.01–0.04 ± 0.01–0.02	Schodl et al. (2022)
Rumination time	SCR recording system (accelerometer)	77,697	0.32 ± 0.01 to 0.45 ± 0.02	Weller and Ezra (2024)

ICAR-IDF Sensor Initiative

currently working on guidelines for rumination data to be efficiently used for breeding and management purposes

All tables included in Brito *et al.* (2025): https://doi.org/10.3168/jds.2025-26554

Sensor-based Fertility Traits

Table 5. Heritability (h^2) estimates for indicators of fertility derived based on automatically recorded data in dairy cattle populations

Trait	Sensor Type	N	Breed	$h^2 \pm$ SE	Reference
Calving to first heat	Herd Navigator (P4)	676	Nordic Red	0.19 ± 0.11	Häggman et al. (2019)
Calving to first heat	Herd Navigator in-line milk progesterone system	2,645	Swedish Red and Holstein	0.18 ± 0.05	Tarekegn et al. (2019)
Commencement of luteal activity	Herd Navigator (P4)	766	Nordic Red	0.24 ± 0.12	Häggman et al. (2019)
Commencement of luteal activity	Herd Navigator in-line milk progesterone system	2,645	Swedish Red and Holstein	0.24 ± 0.04	Tarekegn et al. (2019)
Days from calving to first high-activity episode	Electronic activity tag	517	Holstein, Red Dane, Jersey	0.18 ± 0.07	Løvendahl and Chagunda (2009)
Duration of estrus episode	Electronic activity tag	517	Holstein, Red Dane, Jersey	0.05 ± 0.02	Løvendahl and Chagunda (2009)
Estrus period activity variation	SCR Heatime HR system (accelerometer neck tag)	1,070	Holstein	0.11 ± 0.06	Schöpke and Weigel (2014)
Estrus period average activity	SCR Heatime HR system (accelerometer neck tag)	1,070	Holstein	0.12 ± 0.05	Schöpke and Weigel (2014)
First luteal phase length	Herd Navigator in-line milk progesterone system	2,645	Swedish Red and Holstein	0.08 ± 0.04	Tarekegn et al. (2019)
Interval from calving to first high activity	Automatic milking system (Lely)	8,139	Norwegian Red	0.05 ± 0.01	Heringstad and Wethal (2023)
Interval from commencement of luteal activity to first service	Herd Navigator in-line milk progesterone system	2,645	Swedish Red and Holstein	0.03 ± 0.04	Tarekegn et al. (2019)
Interval from commencement of luteal activity to first service	Herd Navigator in-line milk progesterone system	1,561	Holstein	0.11 ± 0.06	Tenghe et al. (2015)
Length of first interovulatory interval	Herd Navigator in-line milk progesterone system	2,645	Swedish Red and Holstein	0.03 ± 0.04	Tarekegn et al. (2019)
Luteal activity between 25 and 60 DIM	Herd Navigator in-line milk progesterone system	1,561	Holstein	0.06 ± 0.04	Tenghe et al. (2015)
Luteal activity during first 60 DIM	Herd Navigator in-line milk progesterone system	2,645	Swedish Red and Holstein	0.15 ± 0.04	Tarekegn et al. (2019)
MIR-predicted fertility	MIR spectroscopy	4,124	Holstein	0.16 ± 0.03	van den Berg et al. (2021)
Natural log of commencement of luteal activity	Herd Navigator in-line milk progesterone system	1,561	Holstein	0.12 ± 0.05	Tenghe et al. (2015)
Postestrus activity variation	SCR Heatime HR system (accelerometer neck tag)	1,070	Holstein	0.14 ± 0.05	Schöpke and Weigel (2014)
Postestrus average activity	SCR Heatime HR system (accelerometer neck tag)	1,070	Holstein	0.03 ± 0.03	Schöpke and Weigel (2014)
Pre-estrus activity variation	SCR Heatime HR system (accelerometer neck tag)	1,070	Holstein	0.15 ± 0.05	Schöpke and Weigel (2014)
Pre-estrus average activity	SCR Heatime HR system (accelerometer neck tag)	1,070	Holstein	0.05 ± 0.04	Schöpke and Weigel (2014)
Proportion of samples in luteal activity between 25 and 60 DIM	Herd Navigator in-line milk progesterone system	1,561	Holstein	0.12 ± 0.05	Tenghe et al. (2015)
Proportion of samples with luteal activity	Herd Navigator in-line milk progesterone system	2,645	Swedish Red and Holstein	0.13 ± 0.03	Tarekegn et al. (2019)
Regularity of estrus episodes	Electronic activity tag	483	Holstein, Red Dane, Jersey	0.00 ± 0.02	Løvendahl and Chagunda (2009)
Strength of estrus	Electronic activity tag	517	Holstein, Red Dane, Jersey	0.06 ± 0.02	Løvendahl and Chagunda (2009)

Feed Intake, Feeding Behavior, and Feed Efficiency

Table 6. Estimates of heritability (h^2) for traits related to feed intake, feeding behavior, and feed efficiency in dairy cattle populations[1]

Trait	Sensor type or brand	N	Breed	Life stage	$h^2 \pm$ SE	Reference
DMI	Feed bins from Biocontrol (weights for roughage intake)	557	Norwegian Red	Lactating cows	0.29	Bakke and Heringstad (2024)
DMI	Electronic feeder (Gallagher)	1,598 to 1,958	Holstein	Lactating cows	0.19 ± 0.04 to 0.36 ± 0.04	Bolormaa et al. (2023)
DMI	Feed bins, feed gates controlled by neck collars		Holstein	Lactating cows	0.32 ± 0.07 to 0.49 ± 0.08	Byskov et al. (2017)
DMI	Automated feed intake system (recorded in AMS)	3,075	Holstein	Lactating cows (P1)	0.32 ± 0.03	Hardie et al. (2017)
DMI	Automated feed intake system (recorded in AMS)	2,667	Holstein	Lactating cows (multiparous)	0.23 ± 0.03	Hardie et al. (2017)
DMI	Electronic feeder	842	Holstein	Dairy heifers (~6 mo)	0.50 ± 0.09	Lin et al. (2013)
DMI	Cattle Feed Intake System (3D cameras)	2,688	Holstein	Lactating cow	0.25 ± 0.02	Manzanilla-Pech et al. (2023)
DMI	Cattle Feed Intake System (3D cameras)	1,378	Jersey	Lactating cow	0.17 ± 0.03	Manzanilla-Pech et al. (2023)
DMI	Cattle Feed Intake System (3D cameras)	1,951	Nordic Red	Lactating cow	0.18 ± 0.02	Manzanilla-Pech et al. (2023)
DMI	Electronic feed recording system	379	Australian dairy cows	Lactating cows	0.33 ± 0.13	Richardson et al. (2021)
DMI	Electronic feeding system (RIC system, Insentec)	7,379	Holstein	Lactating cows	0.20–0.37	Stephansen et al. (2023)
RFI	Feed bins, feed gates controlled by neck collars		Holstein	Lactating cows	0.23 ± 0.07 to 0.36 ± 0.08	Byskov et al. (2017)
RFI	Derived from automated feed intake, milk yield, and body weight records	2,667 and 3,075	Holstein	Lactating cows	0.13 ± 0.03 and 0.14 ± 0.03	Hardie et al. (2017)
RFI	Electronic feeder (Gallagher)	842	Holstein	Heifers (~6 mo)	0.48 ± 0.09	Lin et al. (2013)
Genetic RFI	Derived from DMI, ECM, and BW data	7,379	Holstein	Lactating cows	0.22–0.34	Stephansen et al. (2023)
Residual energy intake	Derived from AMS records, electronic scale, and n-alkane–based DMI estimates	1,274	Holstein	Lactating cows	0.08 ± 0.03	Hurley et al. (2017)
Residual energy production	Derived from AMS records, electronic scale, and n-alkane–based DMI estimates	1,274	Holstein	Lactating cows	0.24 ± 0.05	Hurley et al. (2017)
Net energy intake	Derived from AMS records, electronic scale, and n-alkane–based DMI estimates	1,274	Holstein	Lactating cows	0.17 ± 0.05	Hurley et al. (2017)
Energy balance	Derived from AMS records, electronic scale, and n-alkane–based DMI estimates	1,274	Holstein	Lactating cow	0.12 ± 0.04	Hurley et al. (2017)
Duration of each feeder visit	Automated intake recording system	1,328	Holstein	Mid-lactation	0.16 ± 0.03	Cavani et al. (2022)
Duration of each meal	Automated intake recording system	1,328	Holstein	Mid-lactation	0.14 ± 0.02	Cavani et al. (2022)
Energy conversion efficiency	Derived from AMS records, electronic scale, and n-alkane–based DMI estimates	1,274	Holstein	Lactating cows	0.17 ± 0.05	Hurley et al. (2017)
Feeding duration	Electronic feeder (Gallagher)	842	Holstein	Heifers (~6 mo)	0.45 ± 0.08	Lin et al. (2013)
Feeding interval	AMF	4,572	Holstein	Calves	0.008 ± 0.01	Graham et al. (2024)
Feeding rate per meal	Automated intake recording system (RIC)	1,328	Holstein	Mid-lactation	0.23 ± 0.03	Cavani et al. (2022)
Feeding rate per visit	Automated intake recording system (RIC)	1,328	Holstein	Mid-lactation	0.11 ± 0.02	Cavani et al. (2022)

Table 6 (Continued). Estimates of heritability (h^2) for traits related to feed intake, feeding behavior, and feed efficiency in dairy cattle populations[1]

Trait	Sensor type or brand	N	Breed	Life stage	$h^2 \pm$ SE	Reference
Intake per meal	Automated intake recording system (RIC)	1,328	Holstein	Mid-lactation	0.13 ± 0.02	Cavani et al. (2022)
Intake per visit	Automated intake recording system (RIC)	1,328	Holstein	Mid-lactation	0.16 ± 0.03	Cavani et al. (2022)
Number of feeder visits per day	Automated intake recording system (RIC; Hokofarm Group)	1,328	Holstein	Mid-lactation	0.16 ± 0.03	Cavani et al. (2022)
Number of meals per day	Automated intake recording system (RIC)	1,328	Holstein	Mid-lactation	0.09 ± 0.02	Cavani et al. (2022)
Number of meals	Electronic feeder (Gallagher)	842	Holstein	Heifers (~6 mo)	0.40 ± 0.09	Lin et al. (2013)
Per-visit milk consumption	AMF	4,572	Holstein	Calves	0.025 ± 0.01	Graham et al. (2024)
Average meal size	Electronic feeder (Gallagher)	842	Holstein	Heifers (~6 mo)	0.46 ± 0.09	Lin et al. (2013)
Daily milk consumption	AMF	10,076	Holstein	Calves	0.07 ± 0.01	Graham et al. (2024)
Daily number of rewarded visits	AMF	10,076	Holstein	Calves	0.03 ± 0.01	Graham et al. (2024)
Daily sum of drinking duration	AMF	10,076	Holstein	Calves	0.07 ± 0.01	Graham et al. (2024)
Drinking duration per visit	AMF	4,572	Holstein	Calves	0.02 ± 0.01	Graham et al. (2024)
Drinking speed	AMF	10,076	Holstein	Calves	0.08 ± 0.01	Graham et al. (2024)
Total consumption variance	AMF	4,572	Holstein	Calves	0.21 ± 0.02	Graham et al. (2024)
Total drinking duration variance	AMF	4,572	Holstein	Calves	0.23 ± 0.02	Graham et al. (2024)
Total duration of feeder visits per day	Automated intake recording system (RIC)	1,328	Holstein	Mid-lactation	0.16 ± 0.03	Cavani et al. (2022)
Total number of visits	AMF	10,076	Holstein	Calves	0.05 ± 0.01	Graham et al. (2024)

[1]3D = 3-dimensional; AMS = automated milking system; AMF = automated milk feeding machine; N = number of cattle; P1 = first parity; RFI = residual feed intake.

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Feed Intake, Feeding Behavior, and Feed Efficiency

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Genetic parameters for feed intake and body weight in dairy cattle using high-throughput 3-dimensional cameras in Danish commercial farms

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THE GLOBAL STANDARD FOR LIVESTOCK DATA

New Calf Traits

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Genetic parameters for calf feeding traits derived from automated milk feeding machines and number of bovine respiratory disease treatments in North American Holstein calves

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Trait development and genetic parameters of resilience indicators based on variability in milk consumption recorded by automated milk feeders in North American Holstein calves

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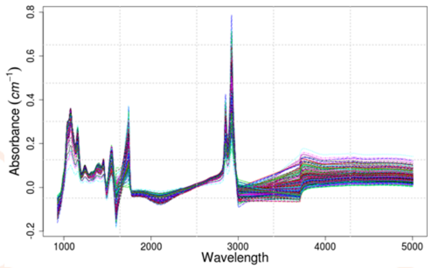
Greenhouse Gas Emissions

Table 7. Heritability estimates for traits related to enteric greenhouse gas emissions by dairy cattle populations

Trait	Technology type or brand	N	Breed	$h^2 \pm SE$	Reference
CH_4 concentration	Nondispersive infrared methane detector installed in the AMS feed bin	1,501	Holstein	0.11 ± 0.03	López-Paredes et al. (2020)
CH_4 concentration, first lactation	Nondispersive infrared CH_4 sensor	489	Holstein	0.10 – 0.28 (±0.05–0.06)	Manzanilla-Pech et al. (2022)
CH_4 concentration, second lactation	Nondispersive infrared CH_4 sensor	368	Holstein	0.13 – 0.29 (±0.05–0.06)	Manzanilla-Pech et al. (2022)
CH_4 concentration	Guardian NG infrared gas monitor installed in the feed bin of the AMS	416	Holstein	0.12 ± 0.01	Saborío-Montero et al. (2020)
CH_4 concentration (log10(CH4))	Nondispersive infrared sensor in AMS	1,508	Holstein	0.11 ± 0.02	van Engelen et al. (2018)
CH_4 concentration (ppm, weekly)	Sniffer	1,800	Holstein	0.32 ± 0.02	van Breukelen et al. (2023)
CH_4 concentration (weekly)	Sniffer	4,664	Holstein	0.17 ± 0.04	van Breukelen et al. (2024)
CH_4 concentration (ppm, daily)	Sniffer	1,800	Holstein	0.18 ± 0.01	van Breukelen et al. (2023)
CO_2 concentration	Nondispersive infrared sensor (SenseAir LPL CH_4/CO_2, Rise Acreo) in AMS	1,508	Holstein	0.12 ± 0.02	van Engelen et al. (2018)
CO_2 concentration (ppm, daily)	Sniffer	1,800	Holstein	0.20 ± 0.01	van Breukelen et al. (2023)
CO_2 concentration (ppm, weekly)	Sniffer	1,800	Holstein	0.32 ± 0.02	van Breukelen et al. (2023)
CH_4 conversion factor	Sniffer method integrated in AMS	182	Holstein	0.13 ± 0.13	Uemoto et al. (2024)
CH_4 intensity	GreenFeed	265	Holstein	0.21 ± 0.14	Kamalanathan et al. (2023)
CH_4 intensity	Noninvasive FTIR analyzer	1,745	Holstein	0.21 ± 0.06	Lassen and Løvendahl (2016)
CH_4 intensity	SF6 tracer and daily milk records (MIR)	379	Australian dairy cows	0.33 ± 0.12	Richardson et al. (2021)
CH_4 production (g/d)	GreenFeed	1,370	Norwegian Red	0.39 ±	Bakke and Heringstad (2024)
CH_4 production	Infrared CH_4 analyzer in milking robot	184	Holstein	0.12–0.45	Breider et al. (2019)
CH_4 production (g/d)	GreenFeed	212	Norwegian Red	0.56 ± 0.20	Heringstad and Bakke (2023)
CH_4 production	GreenFeed	330	Holstein	0.16 ± 0.10	Kamalanathan et al. (2023)
CH_4 production	Milking robot (Fourier transform infrared sensor)	339	Holstein	0.24 ± 0.15	Lassen et al. (2016)
CH_4 production	GreenFeed	451	Holstein	0.36 ± 0.12	Lopes et al. (2024)
CH_4 production	Nondispersive infrared method	1,501	Holstein	0.12 ± 0.04	López-Paredes et al. (2020)
CH_4 production, first lactation	Derived from sensor data (Guardian NG; calculated using ECM and BW)	425	Holstein	0.11 – 0.49 (±0.07–0.13)	Manzanilla-Pech et al. (2022)
CH_4 production, second lactation	Derived from sensor data (Guardian NG; calculated using ECM and BW)	318	Holstein	0.14 – 0.36 (±0.07 – 0.13)	Manzanilla-Pech et al. (2022)
CH_4 production	SF6 tracer method	379	Australian dairy cows	0.16 ± 0.11	Richardson et al. (2021)
CH_4 production	GreenFeed	822	Holstein	0.19 ± 0.02 to 0.33 ± 0.04	van Breukelen et al. (2023)
CO_2 production (g/d)	GreenFeed	822	Holstein	0.24 ± 0.03	van Breukelen et al. (2023)
CH_4 production	FTIR gas analyzer ("sniffer" in AMS)	1,397	Holstein	0.25 ± 0.07	Zetouni et al. (2018)
CH_4 production and intensity predicted from MIR	Milk mid-infrared spectroscopy (MIR)	231,400 to 336,126	Holstein	0.17 ± 0.01 to 0.25 ± 0.01	Kandel et al. (2017)
CH_4 production predicted from MIR	Milk mid-infrared spectroscopy (MIR)	541,565	Holstein	0.23 ± 0.01	Rojas de Oliveira et al. (2024)
CH_4 yield	GreenFeed system	287	Holstein	0.27 ± 0.12	Kamalanathan et al. (2023)
CH_4 yield	SF6 tracer and electronic feed recording system	379	Australian dairy cows	0.23 ± 0.12	Richardson et al. (2021)
CH4_MILK	Milking robot (Fourier transform infrared sensor)	339	Holstein	0.26 ± 0.14	Lassen et al. (2016)
CH4_RATIO	Milking robot (Fourier transform infrared sensor)	339	Holstein	0.09 ± 0.11	Lassen et al. (2016)
CH_4/CO_2 ratio	Sniffer method integrated in AMS	182	Holstein	0.12 ± 0.14	Uemoto et al. (2024)
$CH_4:CO_2$ ratio	Nondispersive infrared sensor (SenseAir LPL CH_4/CO_2, Rise Acreo) in AMS	1,508	Holstein	0.03 ± 0.01	Van Engelen et al. (2018)
CH_4/CO_2 ratio per visit	Sniffer in AMS feed bin	1,746	Holstein	0.01 ± 0.01	van Breukelen et al. (2022)
CH_4/CO_2 ratio per week	Sniffer in AMS feed bin	1,579	Holstein	0.02 ± 0.01	van Breukelen et al. (2022)
Daily CH_4 production	Noninvasive FTIR analyzer	1,745	Holstein	0.21 ± 0.06	Lassen and Løvendahl (2016)



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Body Weight and Udder Conformation

Table 8. Heritability (h^2) estimates for BW and udder conformation traits derived from automatically recorded data

Trait	Sensor type or brand	N	Breed	$h^2 \pm$ SE	Reference
BW	Electronic scale (in AMS)	184	Holstein	0.40–0.67	Breider et al. (2019)
Metabolic BW	Electronic scale (in AMS)	3,075	Holstein	0.51 ± 0.03	Hardie et al. (2017)
Metabolic BW	Electronic scale (in AMS)	2,667	Holstein	0.46 ± 0.03	Hardie et al. (2017)
BW	Cattle Feed Intake System (3D Cameras)	2,688	Holstein	0.51 ± 0.04	Manzanilla-Pech et al. (2023)
BW	Cattle Feed Intake System (3D Cameras)	1,378	Jersey	0.45 ± 0.04	Manzanilla-Pech et al. (2023)
BW	Cattle Feed Intake System (3D Cameras)	1,951	Nordic Red	0.58 ± 0.04	Manzanilla-Pech et al. (2023)
BW	Automated weighing system	7,379	Holstein	0.39–0.52	Stephansen et al. (2023)
Change in BW	Derived from automated weighing system data	7,379	Holstein	<0.02	Stephansen et al. (2023)
Weekly average BW – Lactation 1	Electronic scale (in AMS)	3,253	Holstein	0.31–0.53	Tribout et al. (2023)
Weekly average BW – Lactation 2	Electronic scale (in AMS)	2,553	Holstein	0.43–0.56	Tribout et al. (2023)
BW loss from wk 1 to wk 5 – Lactation 1	Derived from sensor-recorded body weight	3,253	Holstein	0.04	Tribout et al. (2023)
BW loss from wk 1 to wk 5 – Lactation 2	Derived from sensor-recorded body weight	2,553	Holstein	0.02	Tribout et al. (2023)
Udder balance	AMS	4,280	Holstein	0.41 ± 0.02	Medeiros et al. (2024)
Distance front-rear	AMS	4,280	Holstein	0.65 ± 0.02	Medeiros et al. (2024)
Front teat distance	AMS	4,279	Holstein	0.53 ± 0.02	Medeiros et al. (2024)
Rear teat distance	AMS	4,278	Holstein	0.40 ± 0.02	Medeiros et al. (2024)
Udder depth	AMS	4,280	Holstein	0.79 ± 0.01	Medeiros et al. (2024)
Rear teat distance	AMS	12,663	Holstein	0.47 ± 0.02	Poppe et al. (2019)
Front teat distance	AMS	12,663	Holstein	0.60 ± 0.02	Poppe et al. (2019)
Udder depth	AMS	12,663	Holstein	0.69 ± 0.02	Poppe et al. (2019)
Distance front-rear	AMS	12,663	Holstein	0.61 ± 0.02	Poppe et al. (2019)
Udder balance	AMS	12,663	Holstein	0.40 ± 0.02	Poppe et al. (2019)

AMS: automated milking system.

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AMS-based Udder Conformation

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Genetic parameters for udder conformation traits derived from Cartesian coordinates generated by robotic milking systems in North American Holstein cattle

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Trait	Udder depth	Udder balance	Distance front-rear	Front teat distance	Rear teat distance
Udder depth	**0.70(0.01)**	0.11 (0.04)	-0.47 (0.03)	-0.31 (0.03)	-0.27 (0.04)
Udder balance	0.09 (0.02)	**0.41(0.02)**	0.12 (0.04)	-0.20 (0.04)	-0.11 (0.05)
Distance front-rear	-0.40 (0.02)	0.11 (0.02)	**0.65(0.02)**	0.32 (0.03)	0.10 (0.04)
Front teat distance	-0.28 (0.02)	-0.15 (0.02)	0.33 (0.02)	**0.53(0.02)**	0.54 (0.03)
Rear teat distance	-0.22 (0.02)	-0.19 (0.02)	0.15 (0.02)	0.61 (0.01)	**0.40(0.02)**

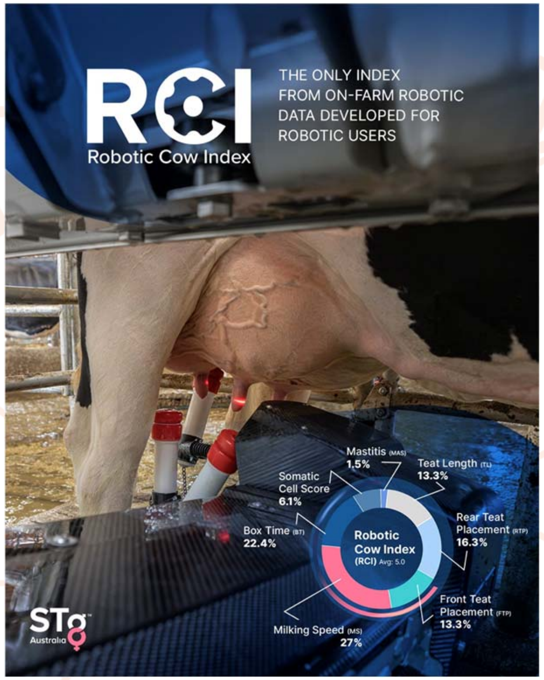
THE GLOBAL STANDARD FOR LIVESTOCK DATA

Milking Efficiency and Milk-related Traits

Table 9. Heritability (h^2) estimates for milking efficiency and milk-related traits derived from automated milking systems (AMS; milking robots) in dairy cattle populations

Trait	N	Breed	h^2 ± SE	Reference
Attachment time	1,899	Holstein	0.25 ± 0.007	Piwczyński et al. (2021)
Average flow rate	1,645	Swedish Holstein	0.37 ± 0.06	Carlström et al. (2013)
Average flow rate	1,512	Swedish Holstein	0.40 ± 0.08	Carlström et al. (2013)
Average flow rate	1,447	Swedish Red	0.37 ± 0.07	Carlström et al. (2013)
Average flow rate	1,544	Swedish Red	0.48 ± 0.08	Carlström et al. (2013)
Milk flow rate	1,714	Holstein	0.55 ± 0.14	Dechow et al. (2020)
Milk harvest rate	1,714	Holstein	0.30 ± 0.10	Dechow et al. (2020)
Average milk flow rate	401	Holstein	0.49 ± 0.06	Gade et al. (2006)
Maximum milk flow rate	401	Holstein	0.55 ± 0.05	Gade et al. (2006)
Average milk flow rate	4,507	Holstein	0.43 to 0.52	Pedrosa et al. (2023)
Maximum milk flow rate	4,507	Holstein	0.47 to 0.58	Pedrosa et al. (2023)
Flow rate	4,883	Norwegian Red	0.48 ± 0.04	Wethal and Heringstad (2019)
Box time	1,645	Swedish Holstein	0.21 ± 0.05	Carlström et al. (2013)
Box time	1,512	Swedish Holstein	0.24 ± 0.07	Carlström et al. (2013)
Box time	1,447	Swedish Red	0.38 ± 0.06	Carlström et al. (2013)
Box time	1,544	Swedish Red	0.44 ± 0.07	Carlström et al. (2013)
Box time	1,053	Swedish Holstein	0.24	Carlström et al. (2014)
Box time	1,749	Swedish Red	0.45	Carlström et al. (2014)
Box time	2,258	Holstein	0.25 ± 0.05	Løvendahl and Buitenhuis (2022)
Box time	2,407	Jersey	0.27 ± 0.05	Løvendahl and Buitenhuis (2022)
Box time	1,486	Holstein	0.21 ± 0.03	Sitkowska et al. (2024)
Box time	4,883	Norwegian Red	0.27 ± 0.03	Wethal and Heringstad (2019)
Connection time	27,726	Danish Holstein (including Danish Red Holstein)	0.36 ± 0.02	Stephansen et al. (2018)
Handling time	4,883	Norwegian Red	0.05 ± 0.01	Wethal and Heringstad (2019)
Incomplete milkings	1,714	Holstein	0.03 ± 0.01	Dechow wt al. (2020)
Incomplete milkings	4,883	Norwegian Red	0.01 ± 0.005	Wethal and Heringstad (2019)
Leakage	66,743	Norwegian Red	0.04 ± 0.01	Wethal et al. (2020)
Milk yield	1,713	Holstein	0.25 ± 0.05	Aerts et al. (2021)
305-d mature-equivalent milk yield	1,714	Holstein	0.30 ± 0.02	Dechow et al. (2020)
Milk yield (5 to 70 d postpartum)	670	Nordic Red	0.29 ± 0.13	Häggman et al. (2019)
Milk yield	401	Holstein	0.20 ± 0.03	Gade et al. (2006)
Daily milk yield	953	Holstein	0.14–0.20	Nixon et al. (2009)
Daily milk yield	4,507	Holstein	0.07 to 0.28	Pedrosa et al. (2023)
Daily milking frequency	953	Holstein	0.02–0.08	Nixon et al. (2009)
Milking efficiency	4,506	Holstein	0.45 to 0.56	Pedrosa et al. (2023)
Milking frequency	1,713	Holstein	0.23 ± 0.04	Aerts et al. (2021)
Milking failures	4,511	Holstein	0.02 ± 0.01	Pedrosa et al. (2023)
Milking efficiency	1,486	Holstein	0.35 ± 0.01	Sitkowska et al. (2024)
Milking efficiency	4,883	Norwegian Red	0.22 ± 0.03	Wethal and Heringstad (2019)
Milking frequency	2,258	Holstein	0.22 ± 0.04	Løvendahl and Buitenhuis (2022)
Milking frequency	2,407	Jersey	0.17 ± 0.04	Løvendahl and Buitenhuis (2022)
Milking frequency	1,899	Holstein	0.51 ± 0.01	Piwczyński et al. (2021)
Milking frequency	4,883	Norwegian Red	0.05 ± 0.01	Wethal and Heringstad (2019)
Milking frequency (DIM 0–99 d)	1,216	not informed (Dairy Cattle)	0.16 ± 0.04	König et al. (2006)
Milking frequency (DIM 100–199 d)	1,112	not informed (Dairy Cattle)	0.19 ± 0.05	König et al. (2006)
Milking frequency (DIM 200–299 d)	1,004	not informed (Dairy Cattle)	0.22 ± 0.05	König et al. (2006)
Test-day milking frequency	543	Holstein	0.14 ± 0.01	Nixon et al. (2009)
Milking interval	1,645	Swedish Holstein	0.26 ± 0.05	Carlström et al. (2013)
Milking interval	1,512	Swedish Holstein	0.17 ± 0.05	Carlström et al. (2013)
Milking interval	1,447	Swedish Red	0.09 ± 0.03	Carlström et al. (2013)
Milking interval	1,544	Swedish Red	0.23 ± 0.05	Carlström et al. (2013)
Milking interval	4,883	Norwegian Red	0.02 ± 0.01	Wethal and Heringstad (2019)
Milking refusals	4,511	Holstein	0.09 ± 0.01	Pedrosa et al. (2023)
Milking speed	1,713	Holstein	0.42 ± 0.07	Aerts et al. (2021)
Milking speed	1,899	Holstein	0.43 ± 0.01	Piwczyński et al. (2021)
Milking speed	1,486	Holstein	0.36 ± 0.05	Sitkowska et al. (2024)
Milking speed	72,487	Norwegian Red	0.22 ± 0.01	Wethal et al. (2020)
Milking time	1,714	Holstein	0.26 ± 0.04	Dechow et al. (2020)
Milking time	401	Holstein	0.38 ± 0.03	Gade et al. (2006)
Milking time	4,507	Holstein	0.22 to 0.28	Pedrosa et al. (2023)
Milking time	1,899	Holstein	0.31 ± 0.01	Piwczyński et al. (2021)

An example →



All tables included in Brito *et al.* (2025): https://doi.org/10.3168/jds.2025-26554

Data Access, Ownership, Storage, and Infrastructure

- ✓ National genetic evaluations: **robust and scalable infrastructure** capable of handling large and multidimensional datasets (Wangen *et al.,* 2021)
- ✓ Definition of the **variables and data that should be stored for long-term usage** to ensure consistency, relevance, and efficiency in genetic evaluations
- ✓ **Challenges:** data **integrity, security, and accessibility** while maintaining **computational efficiency** for real-time or near-real-time analyses
- ✓ High-throughput **storage solutions**: distributed databases and cloud-based platforms

Data Access, Ownership, Storage, and Infrastructure

- ✓ **Standardized data formats** are necessary: ICAR plays a major role on this regard
- ✓ **Regulatory considerations**: data access and portability rights, data access modalities, data storage (format, resolution), robust data security, and ethical considerations
- ✓ **Various regulatory frameworks**: General Data Protection Regulation, Data Act, Data Governance Act
- ✓ Transparent policies as well as **clear and fair data sharing agreements** are needed to ensure **optimal use and equitable value distribution** among all stakeholders

Roadmap for Implementation: Points to Consider

- ✓ Dairy farmers may seek to monetize their data: agreements with research organizations, national genetic evaluation centers, or even selling their data to private dairy breeding companies
- ✓ Develop centralized and **producer-owned databases**
- ✓ Automate data cleaning, processing, and integration pipelines, **including through AI tools**
- ✓ Regularly **re-estimate variance components** as datasets expand and data sources are added
- ✓ Continue refining **selection indexes** by incorporating sensor-derived sustainability traits
- ✓ Continued training of the **next generation of professionals** (throughout the whole dairy chain)

Conclusions

- ✓ Sensor technologies provide powerful opportunities to improve health, welfare, efficiency, and overall sustainability of dairy cattle breeding programs
- ✓ Success depends on:
  - Fair data governance and sharing agreements across stakeholders
  - Integration, standardization, and harmonization of datasets
  - Robust data cleaning, validation, and quality control
  - Centralized platforms and collaborations among key stakeholders at the (inter)national level

Thank You!

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ICAR

FIL IDF Fédération Internationale du Lait • International Dairy Federation

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Invited Review
Genetics

Genomics and phenomics: Who will be the dairy cows of the future?

Luiz F. Brito,* Allan P. Schinckel, and Hinayah Rojas de Oliveira

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Invited review: Using data from sensors and other precision farming technologies to enhance the sustainability of dairy cattle breeding programs

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