BOVI-ANALYTICS

CornellCALS
College of Agriculture and Life Sciences

# How artificial intelligence can transform an entire dairy industry, or NOT?

1982 - 2006 → AI → DATA → LIFECYCLE

*Challenges and opportunities*

Associate Prof. Dr. DVM Miel Hostens
Robert and Anne Everett Endowed Associate Professor of Digital Dairy Management and Data Analytics

# Let me introduce you ‘Maria Paula Minne’

- Born in 1924 between WWI and II in Belgium
- She had 9 children (of which 7 survived)
- She went to school until she was 14
- She spoke only 1 language
- She was a small-holder dairy farmer milking 4 cows by hand, with some of her best cows producing 15-20 L of milk at peak lactation (3000L/305d)
  - No access to nutritional knowledge
  - Little access to genetics
  - **Little access to technology**
  - **She did not feel responsible for the planet**

# Let me introduce you ‘Miel Maria Paula Minne’

Per year:
3.500 calls
10 000 bombs
250 tonne
550 000 lbs

# Let me introduce you ‘Miel Maria Paula Gabriel Hostens’

Born in Belgium in 1982

- Spend my holidays at my grandmothers farm
- Spend my evenings at home destroying my parents first Macintosh & Intel 2.86

Veterinary MSc (2006) & PhD (2012)

- Unlimited access to nutritional knowledge
- Unlimited access to best cow genetics
- **Unlimited access to innovation/technology/AI**

I speak 5 different natural languages and over 5 computer languages

I work with both small-holder and some of the largest dairies around the world

**I feel extremely responsible for this planet**

**I have 2 children**

# Disclosure - I'm academic entrepreneur

- In 2013, a prototype of data warehouse architecture was bought by Delaval (DairyDataWarehouse). MILK SUSTAINABILITY CENTER
- 
- In 2018, I co-founded a company to integrate data from the dairy industry in the cloud called MmmooOgle (used by VYLA, SPADE, FARM-ES).

- In 2026, a new startup in secure and privacy preserving fusion of dairy data with AI is going to be launched

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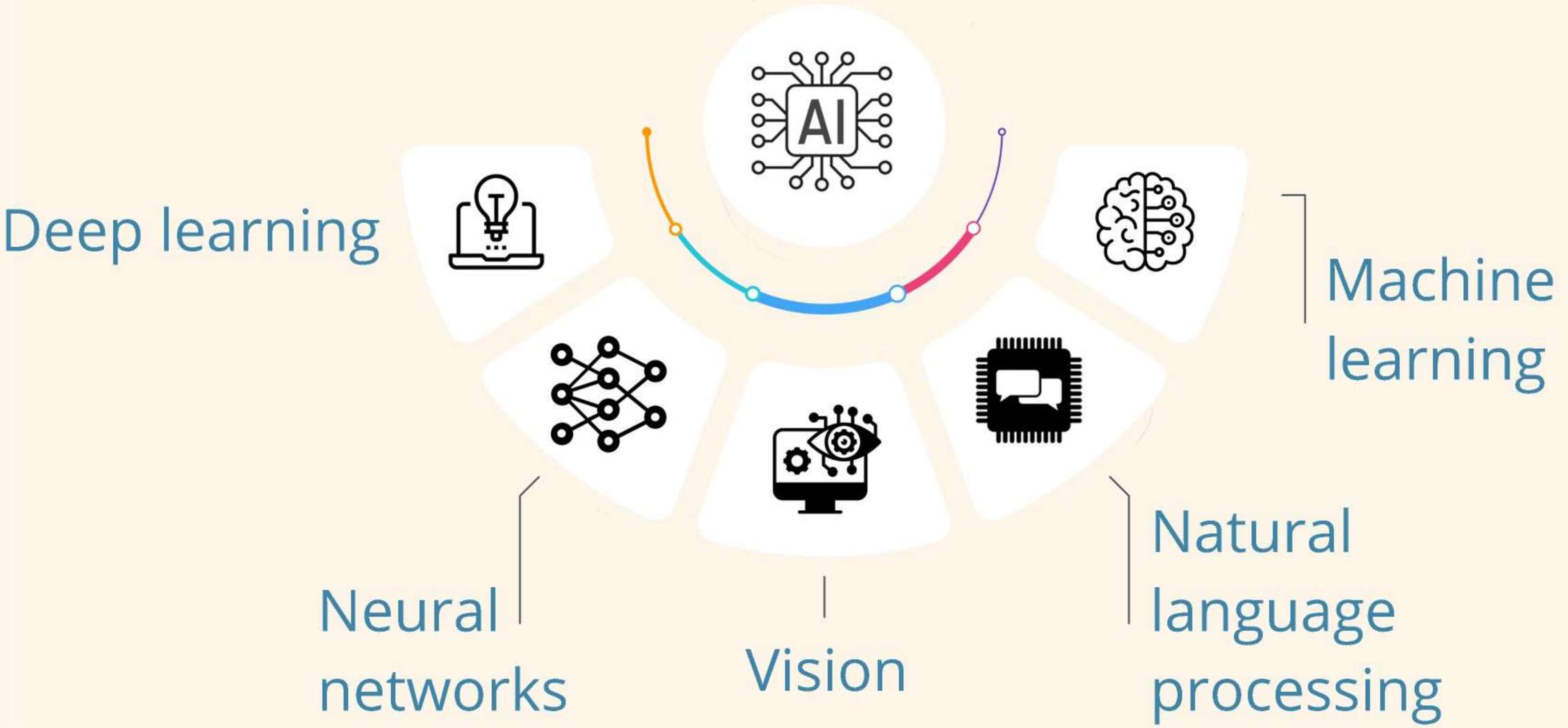
# Many of the techniques are based on neuroscience



# Different types of artificial intelligence

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# Different types of artificial intelligence

*First, neurons starts processing features, and differences between features to detect objects visually*

***UNSUPERVISED LEARNING***

# Different types of artificial intelligence

*First, neurons starts processing features, and differences between features to detect objects visually*

***UNSUPERVISED LEARNING***

*Next, those neurons learn to associate specific words with those objects*

***SUPERVISED LEARNING***

# Different types of artificial intelligence

*First, neurons starts processing features, and differences between features to detect objects visually*

***UNSUPERVISED LEARNING***

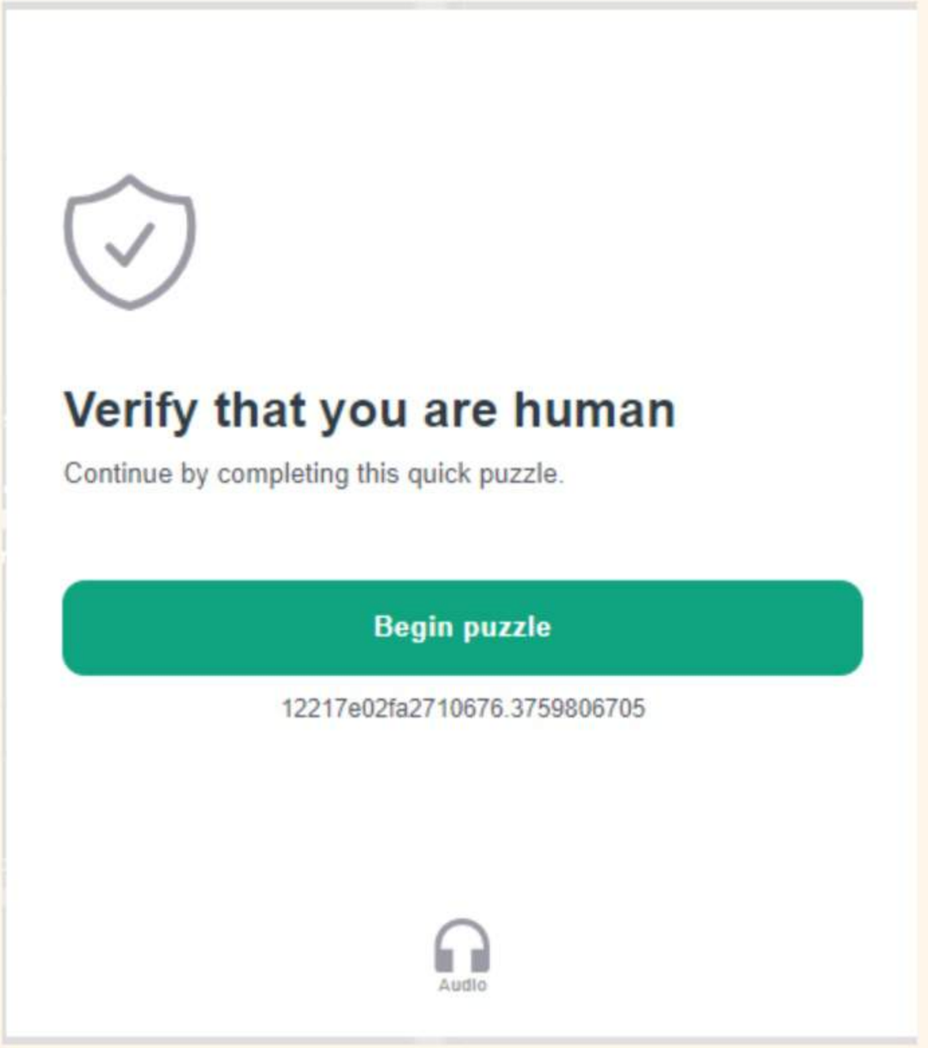
*Next, those neurons learn to associate specific words with those objects*

***SUPERVISED LEARNING***

*Last, those neurons learn to do or not do specific things with the object based on its own experience*

***REINFORCEMENT / ACTIVE LEARNING***

# Different types of artificial intelligence

# The core infrastructure of Artificial Intelligence

## Cloud

Centralized data centers providing scalable resources for massive model training and complex storage.

## Edge

Local processing on devices (phones, IoT) for low latency, privacy, and reduced bandwidth usage.

## Compute

The raw processing power, primarily GPUs and TPUs, required to execute billions of calculations per second.

## Storage

High-speed data repositories holding trillions of tokens and parameters needed for model intelligence.

# The Birth of Generative Models

## 1. Transformers

A neural network architecture that uses "attention" to understand context and relationships in data.

## 2. Large-Scale Pre-training

Models digest massive amounts of internet text to predict the next word, learning grammar and logic.

# Training GPT-3: The environmental cost

## 1,287 MWh

~ 120 US homes annual electricity consumed during the training phase.

## 552 Tons

Metric tons of $CO_2e$ emitted into the atmosphere.

## 700,000 L / 185,000 gallons

Water consumed for data center cooling.

## 112 Cars

Equivalent to annual emissions of gasoline-powered vehicles.

# Training GPT-3 or GPT-5

| Model | Energy | Water | $CO_2$ |
|---|---|---|---|
| GPT-3 | ~1.3 GWh | ~0.7M L | ~500 t |
| GPT-5 (low est.) | ~3–5 GWh | millions L | few thousand t |
| GPT-5 (high est.) | ~80–100 GWh | tens of millions L | 20k–30k t |

# Perspective: AI vs. Dairy Industry

### GPT-3 Training (One-time)

**502 - 552**

Metric Tons CO2e

A high-intensity computing event, but represents a specific phase of development.

### Dairy Operations (Ongoing)

**~112 Cows**

Annual CO2e per year

Global milk production accounts for 2.2% of all GHG emissions (2.2 MtCO2e in some regions).

While training a single model is equivalent to **600,000 kg / 1,322,773 lbs of milk production**, the dairy industry's emissions are continuous and significantly higher on a global annual scale.

# AI prompts vs others

| Action / Item | Energy | Water | $CO_2$ |
|---|---|---|---|
| AI prompt | ~0.3 Wh | ~0.0003–0.025 L | ~0.03 g |
| Email | ~0.5 Wh | ~1–10 mL | ~0.3 g |
| Spotify song | ~2–8 Wh | ~10–50 mL | ~1–5 g |
| Milk (250 mL) | ~200–500 Wh | ~200–300 L | ~600–800 g |
| Egg | ~100–200 Wh | ~150–200 L | ~200–300 g |
| Chicken (100 g) | ~500–1,000 Wh | ~400–600 L | ~500–1,000 g |
| Beef burger | ~2,000–4,000 Wh | ~1,800–7,000 L | ~2,000–4,000 g |

# Data

Farm mgmt systems

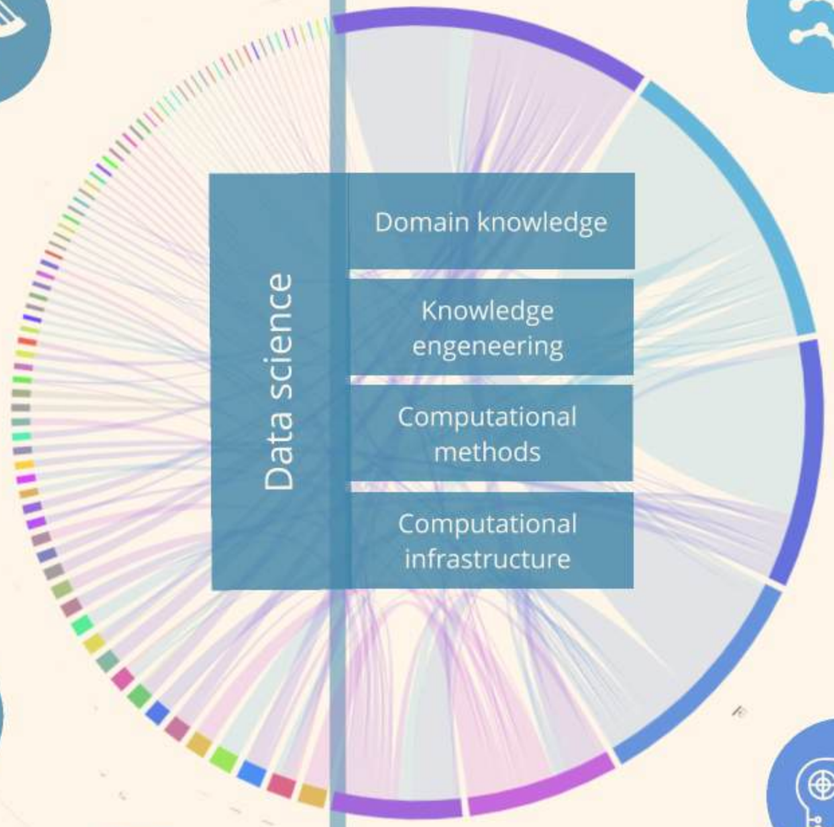
Omics

Bio-markers

PLF Wearables

Vision

Precision agriculture




# Knowledge Wisdom

Real world evidence

P = G x E

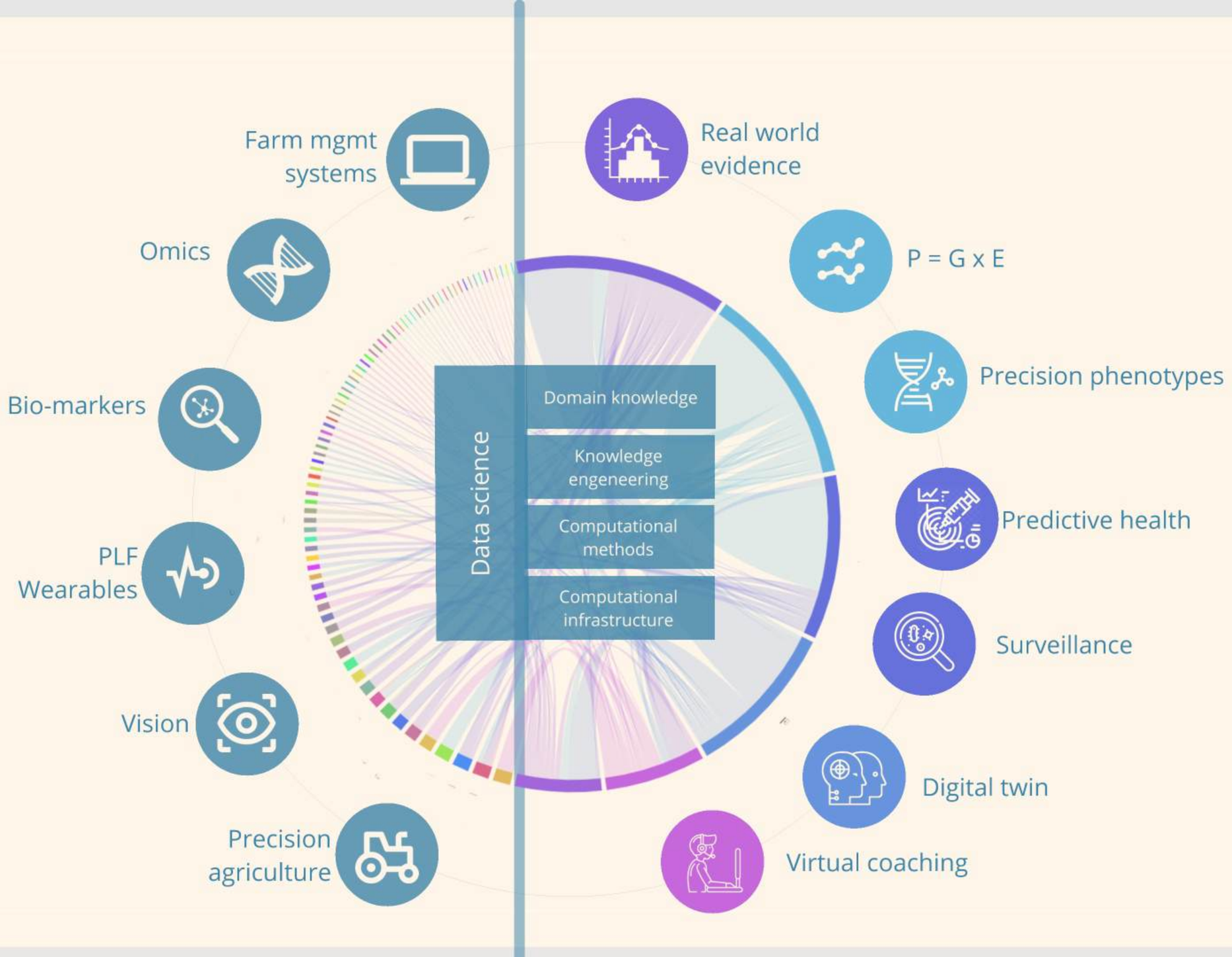
Precision phenotypes

Predictive health

Surveillance

Digital twin

Virtual coaching


Farm mgmt systems
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Data science
Domain knowledge
Knowledge engeneering
Computational methods
Computational infrastructure

Farm mgmt systems

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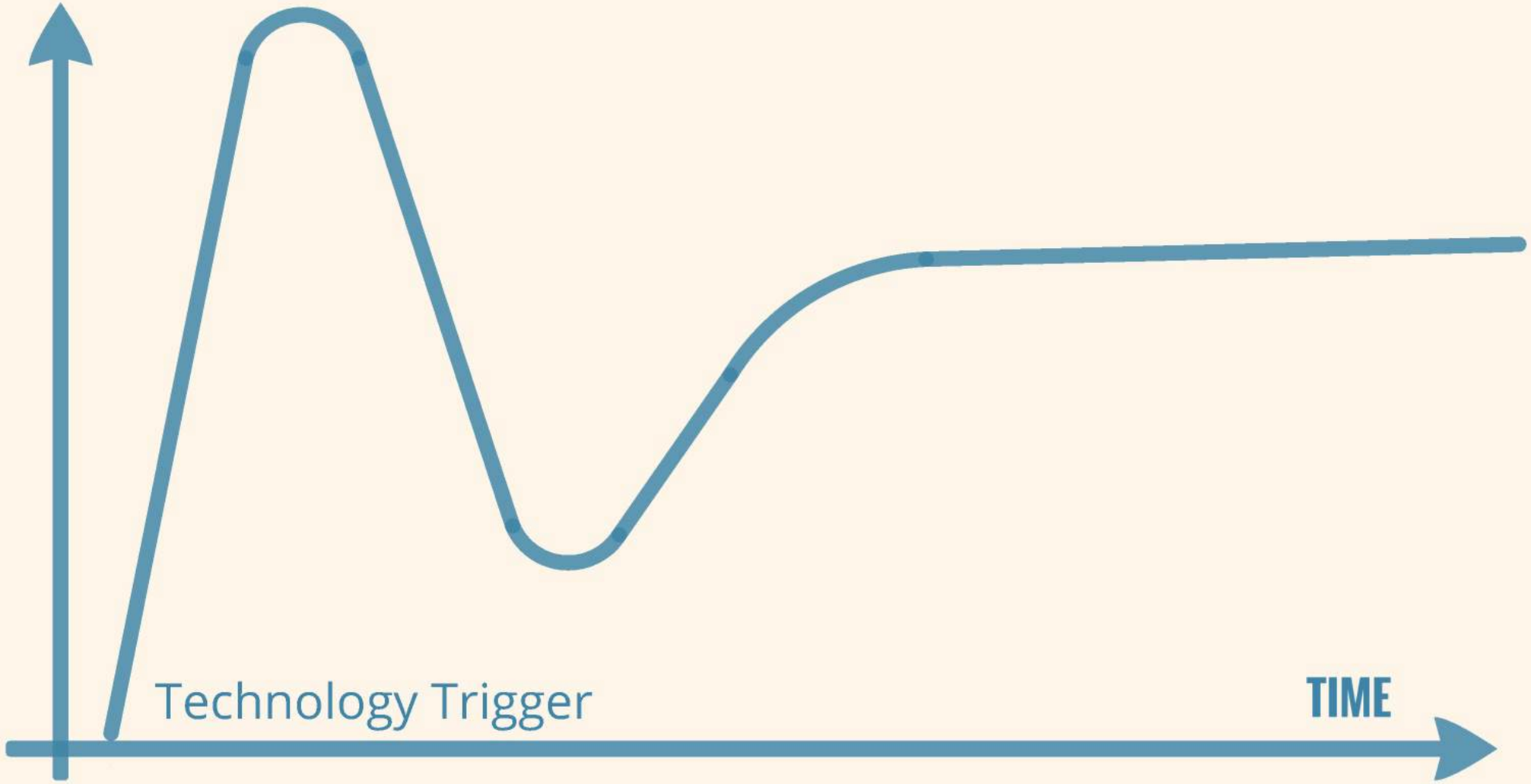
# Gartner hypecycle for AI in agriculture

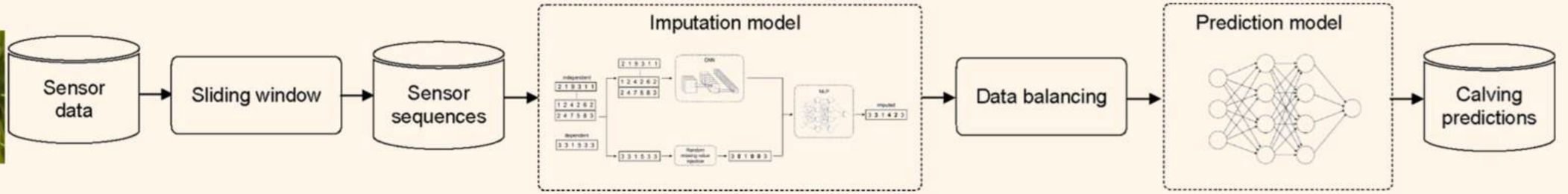


# Predictive health for decision support

Computers and Electronics in Agriculture
Volume 191, December 2021, 106566

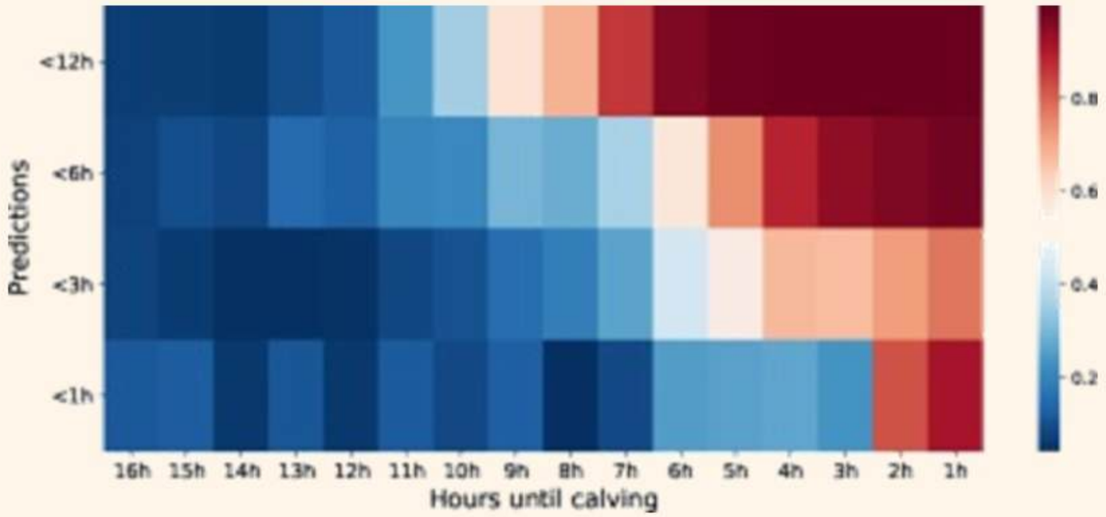
## Leveraging sequential information from multivariate behavioral sensor data to predict the moment of calving in dairy cattle using deep learning

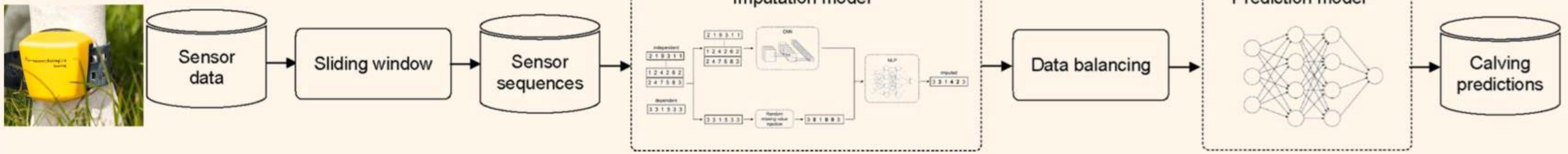
Arno Liseune [a], Dirk Van den Poel [a], Peter R. Hut [c], Frank J.C.M. van Eerdenburg [c], Miel Hostens [b c]



# Predictive health for decision support

Fig. 6. The predicted probabilities of the 12 h, 6 h, 3 h and 1 h calving models for different time periods until calving.

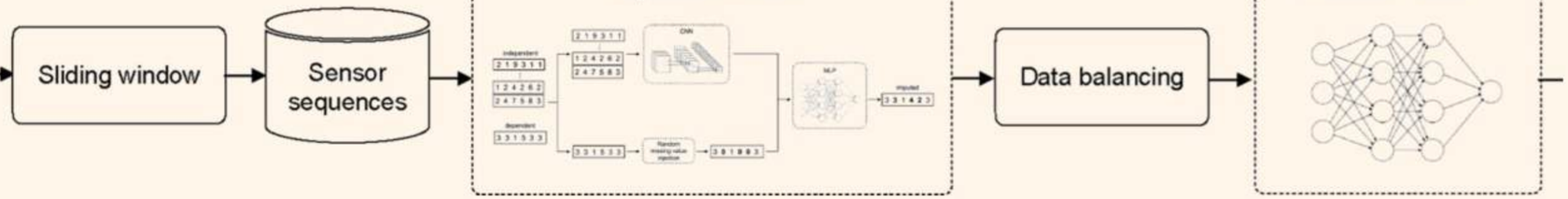


# Metabolic predictions

## A predictive model for hypocalcaemia in dairy cows utilizing behavioural sensor data combined with deep learning

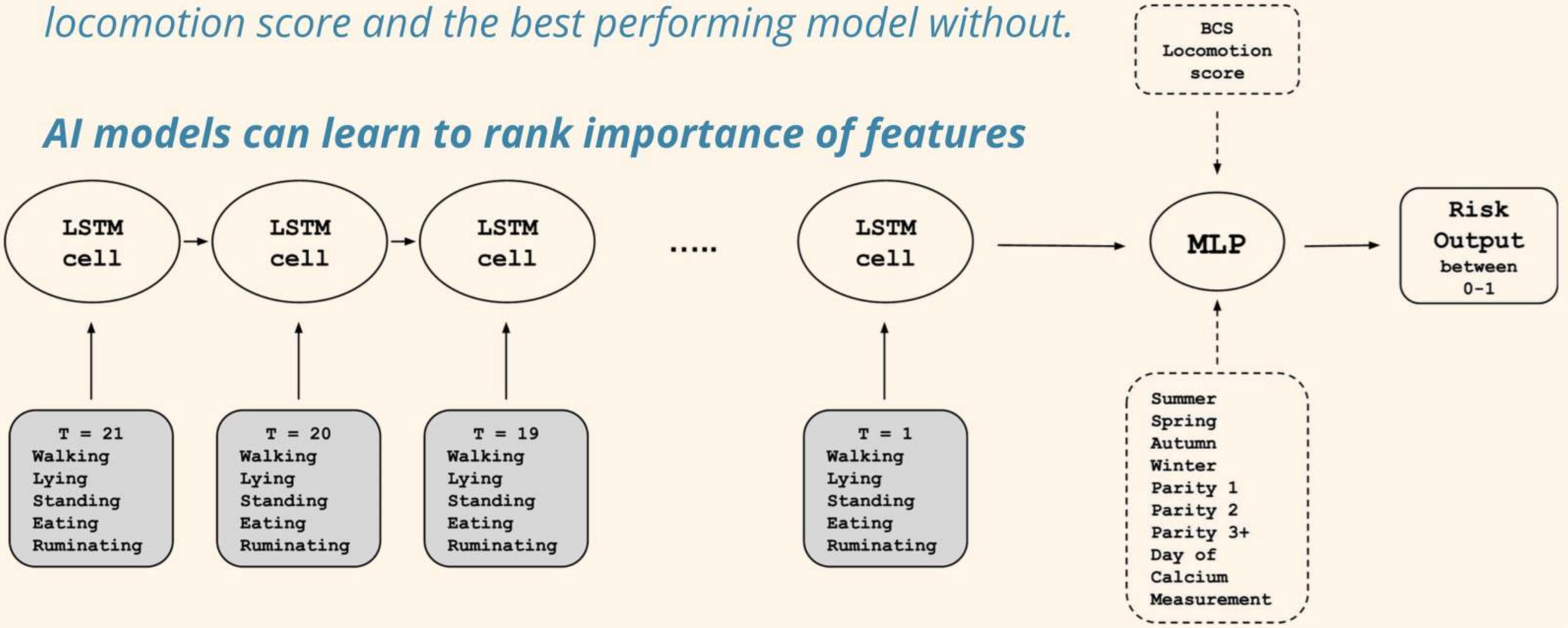
Meike van Leerdam [a], Peter R. Hut [a], Arno Liseune [b], Elena Slavco [a], Jan Hulsen [c], Miel Hostens [a d]



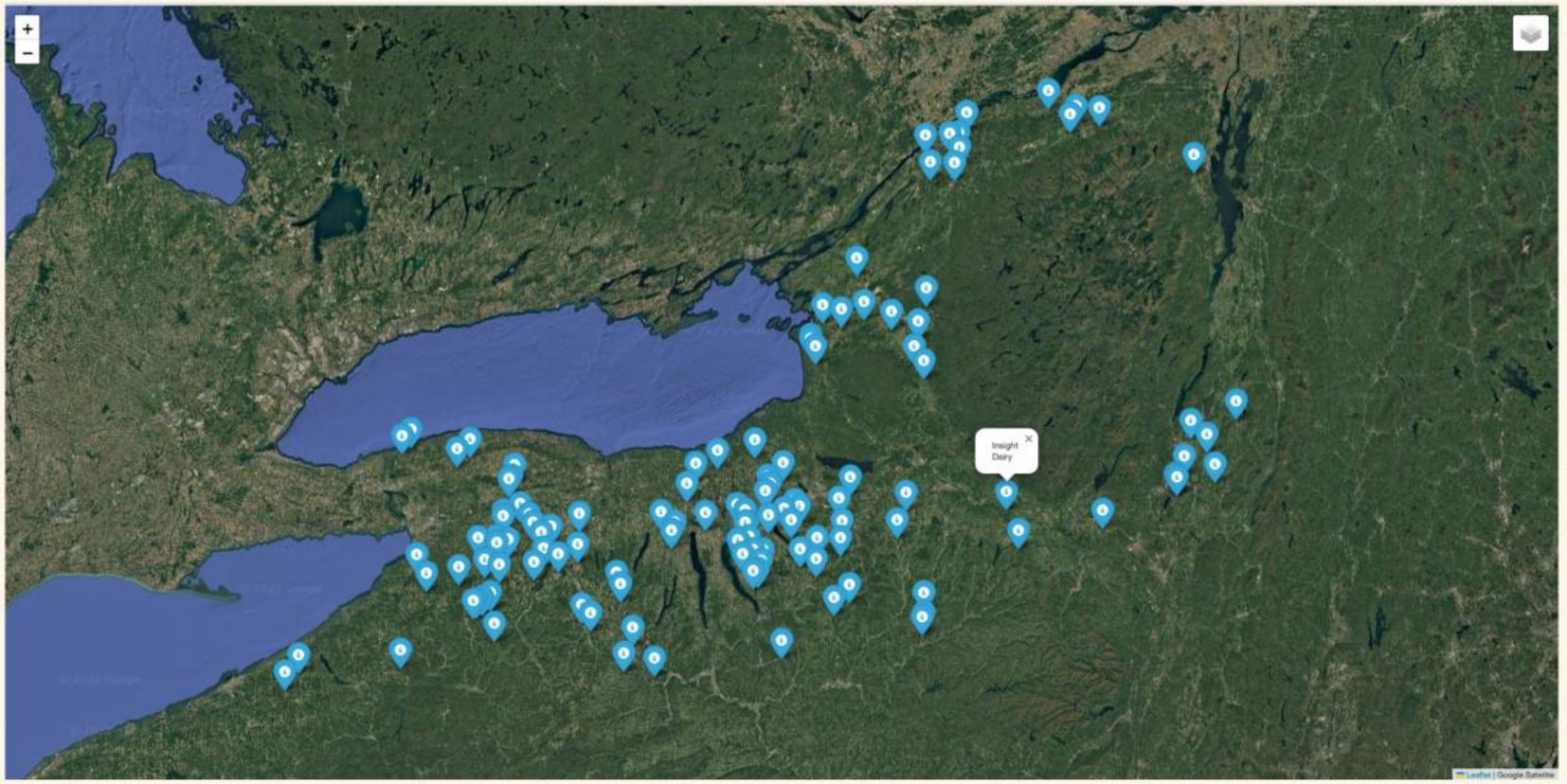

# Metabolic predictions

*!!! There was no significant difference in mean AUC between the best performing model with BCS and locomotion score and the best performing model without.*

***AI models can learn to rank importance of features***



# Automated feature extraction

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# Automated feature extraction


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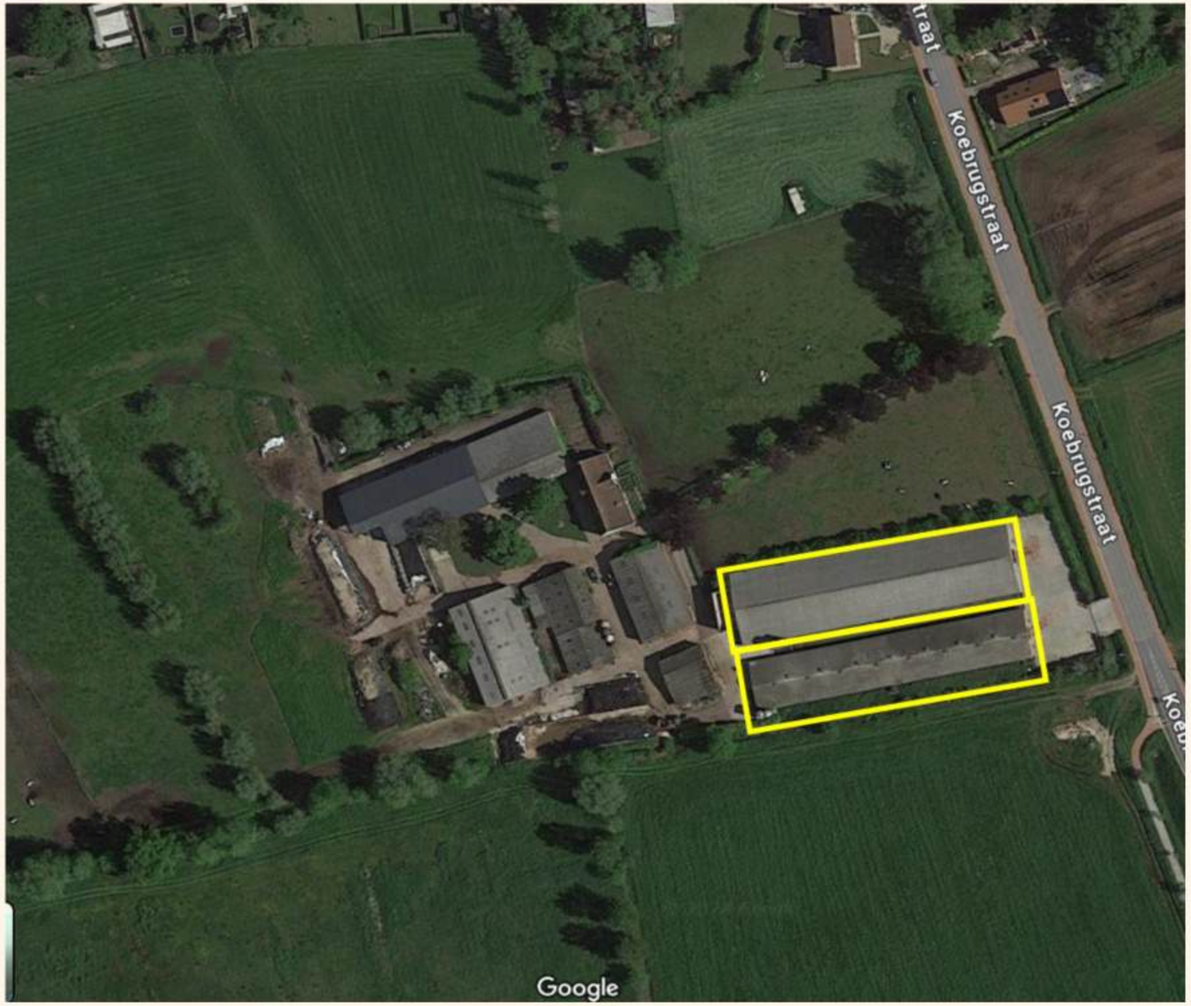
# Automated feature extraction




*Automated orientation of the barn detected as feature to predict disease outbreak*

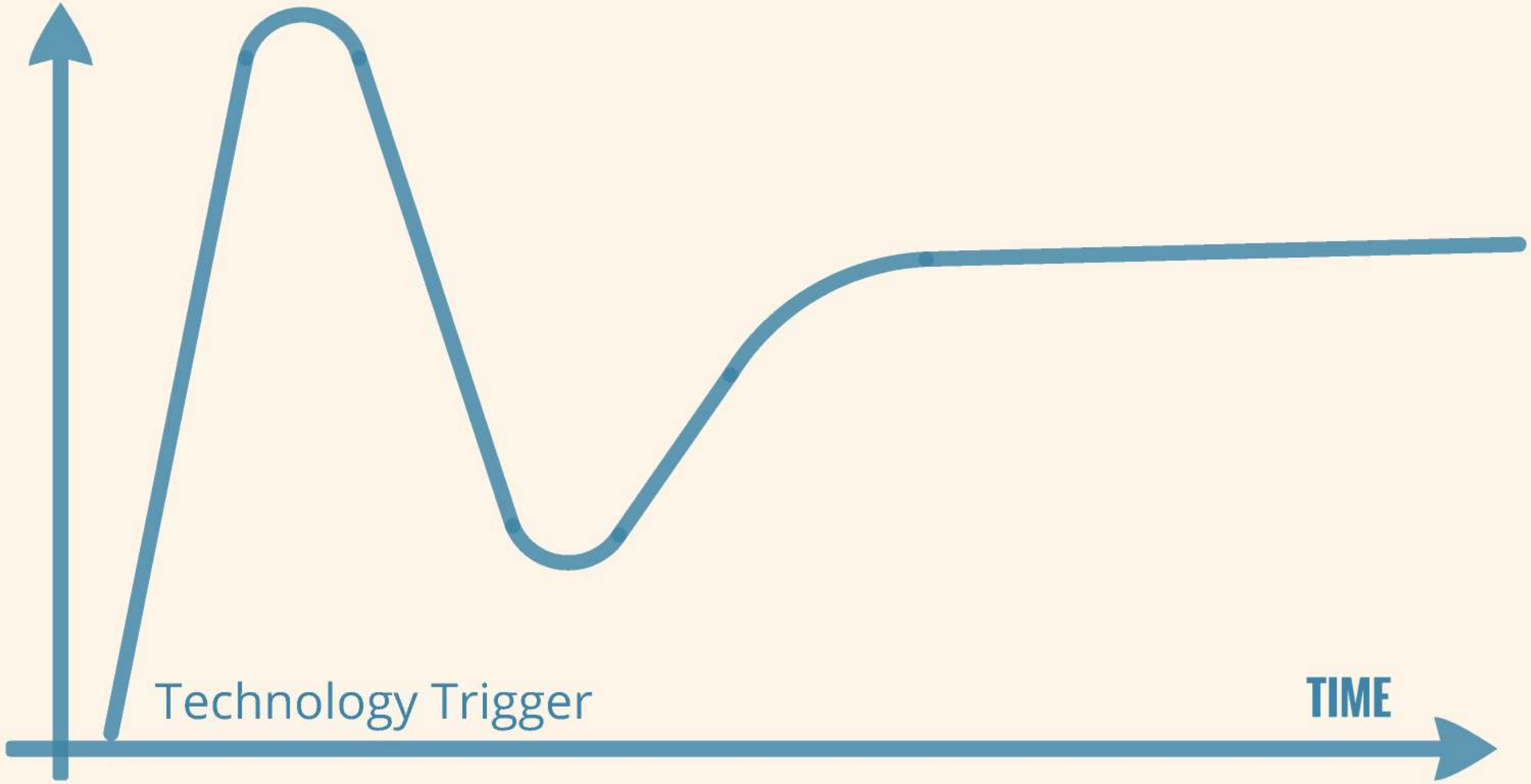
DECIDE

# Precision phenotypes


11/06/2024 16:00:08
CH4
COW_3 19 (SEMI-AUTO)
Playing Behaviour: false

# Precision phenotypes

# Technology trigger is definitely present



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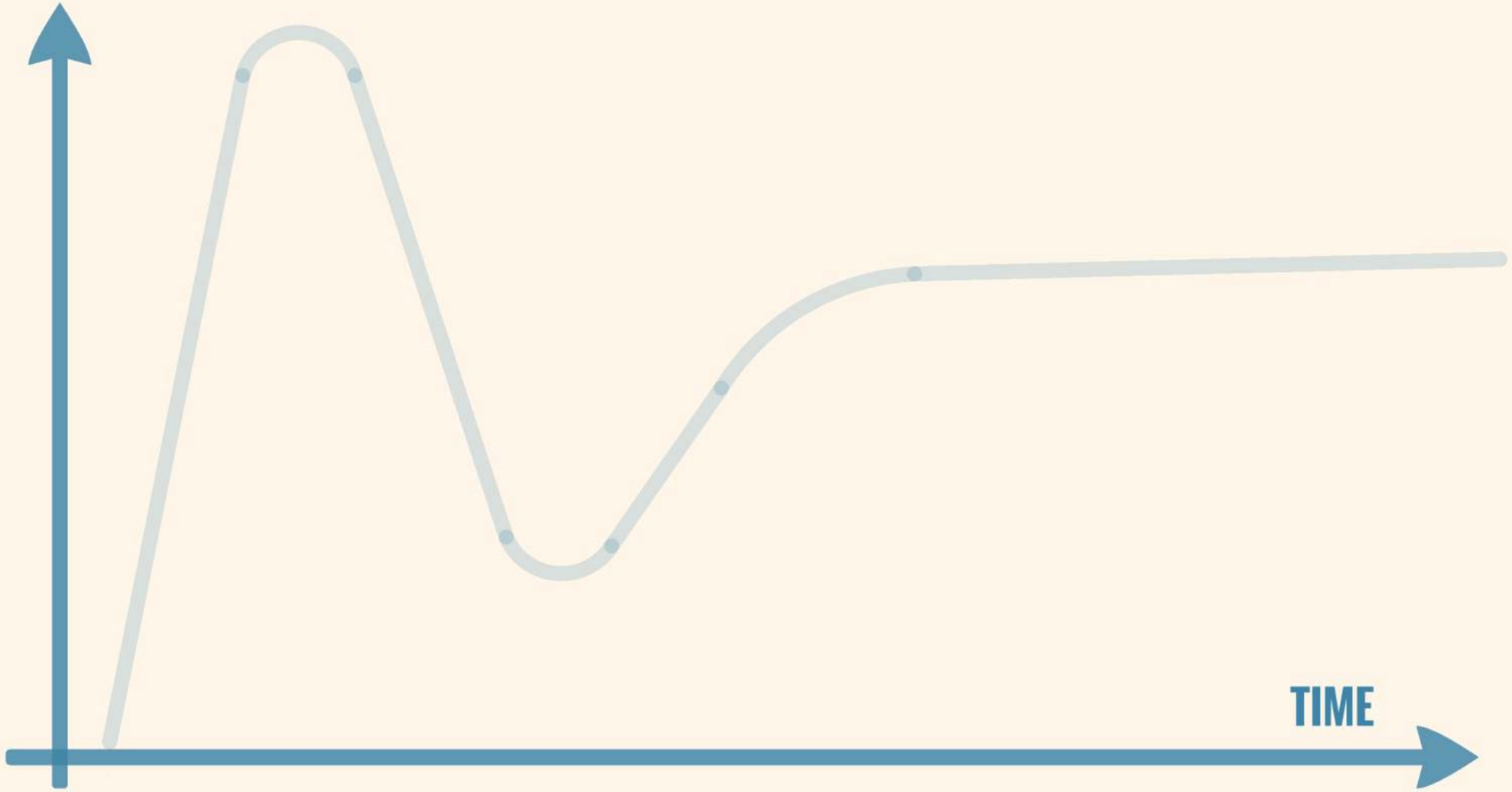
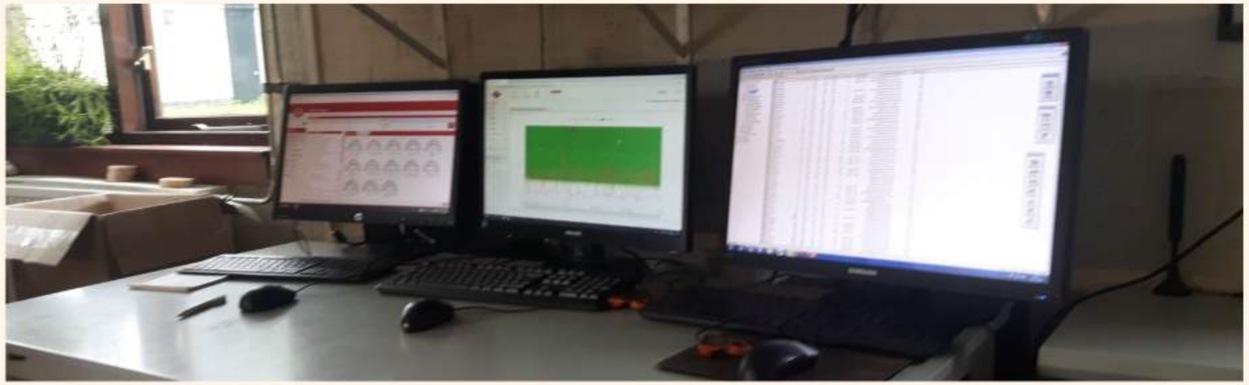
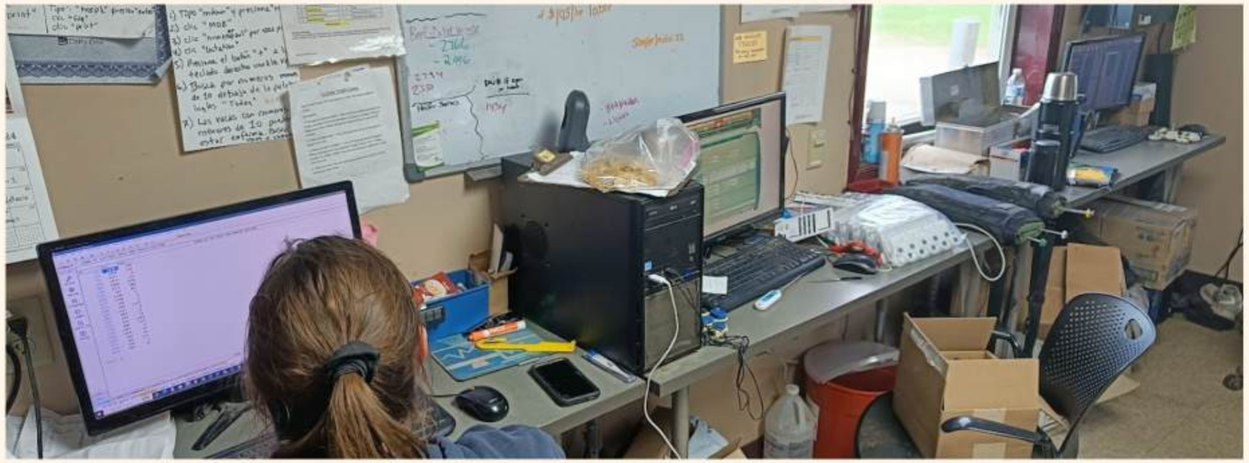
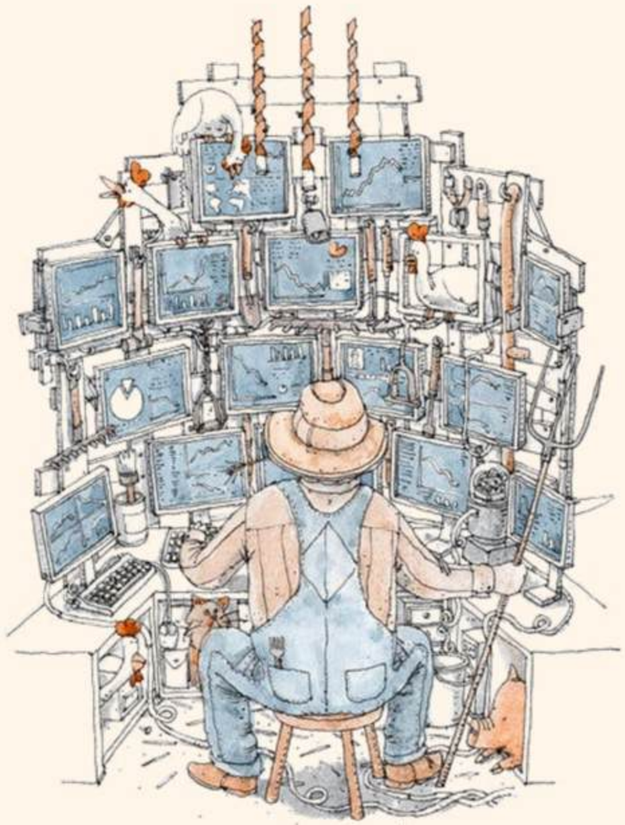
# What can AI learn from the ('Big') Data hypecycle



# Data - integration is the key







# Identification is a must have, not a nice to have



*Being able to predict I'm sick/ calving/lame is not enough, you need to be sure who I am*

# Joint initiatives on standardisation

J. Dairy Sci. TBC
https://doi.org/10.3168/jds.2025-26554


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

Luiz F. Brito,[1*] Bjørg Heringstad,[2] Ilka Christine Klaas,[3] Katharina Schodl,[4] Victor E. Cabrera,[5] Anna Stygar,[6] Michael Iwersen,[7] Marie J. Haskell,[8] Kathrin F. Stock,[9] Nicolas Gengler,[10] Jeffrey Bewley,[11] Miel Hostens,[12] Elsa Vasseur,[13] and Christa Egger-Danner[4]

# Academic shift towards AI needed

## Prediction of persistency for day 305 of lactation at the moment of the insemination decision

Yongyan Chen*, Wilma Steeneveld, Mirjam Nielen and Miel Hostens

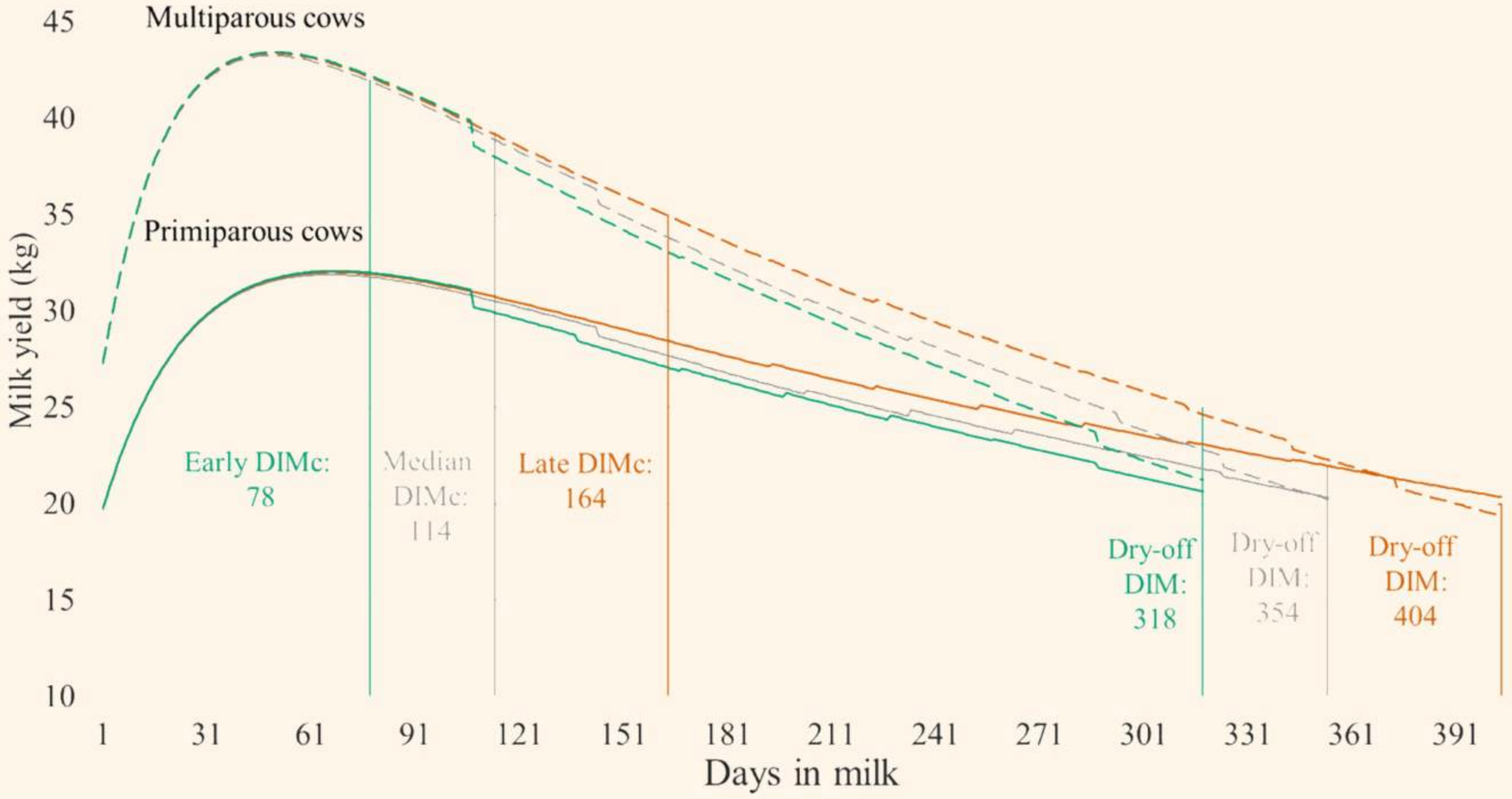
Department of Population Health Sciences, Faculty of Veterinary Medicine, Utrecht University, Utrecht, Netherlands

J. Dairy Sci. 107:5794–5804
https://doi.org/10.3168/jds.2023-24282

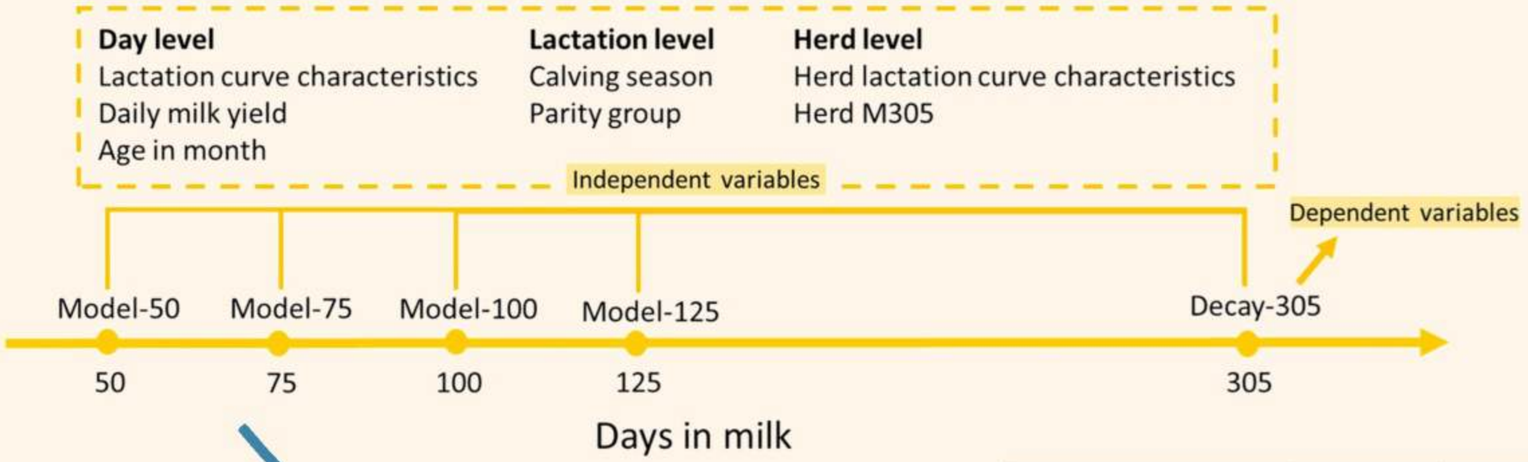

## Association between days post-conception and lactation persistency in dairy cattle

Y. Chen,[1]* W. Steeneveld,[1] K. Frankena,[2] I. Leemans,[2] H. Aardema,[1] P. L. A. M. Vos,[1] M. Nielen,[1] and M. Hostens[1]
[1]Department of Population Health Sciences, Faculty of Veterinary Medicine, Utrecht University, 3584 CL Utrecht, the Netherlands
[2]Department of Animal Science, Adaptation Physiology Group, Wageningen University & Research, 6700 AH Wageningen, the Netherlands

# Academic shift towards AI needed



# Academic shift towards AI needed




*!!! We need to allow people to publish low prediction accuracy*

| Insemination moment (day) | $R^2$ | RMSE | MAE | MAPE |
|---|---|---|---|---|
| 50 | 0.266 | $7.73*10^{-4}$ | $6.16*10^{-4}$ | 0.391 |
| 75 | 0.270 | $7.51*10^{-4}$ | $5.98*10^{-4}$ | 0.400 |
| 100 | 0.325 | $7.22*10^{-4}$ | $5.72*10^{-4}$ | 0.371 |
| 125 | 0.407 | $6.60*10^{-4}$ | $5.22*10^{-4}$ | 0.370 |

[1] Model performance indicators: $R^2$, coefficient of determination; RMSE, root mean squared error; MAE, mean absolute error; MAPE, mean absolute percentage error.

# Academic shift towards AI needed


*There is a graveyard of academic models because science rewards novelty over sustainibility*

# First signals


Radiology Case Reports 19 (2024) 2106–2111

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Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/radcr

RCR RADIOLOGY CASE REPORTS

Case Report

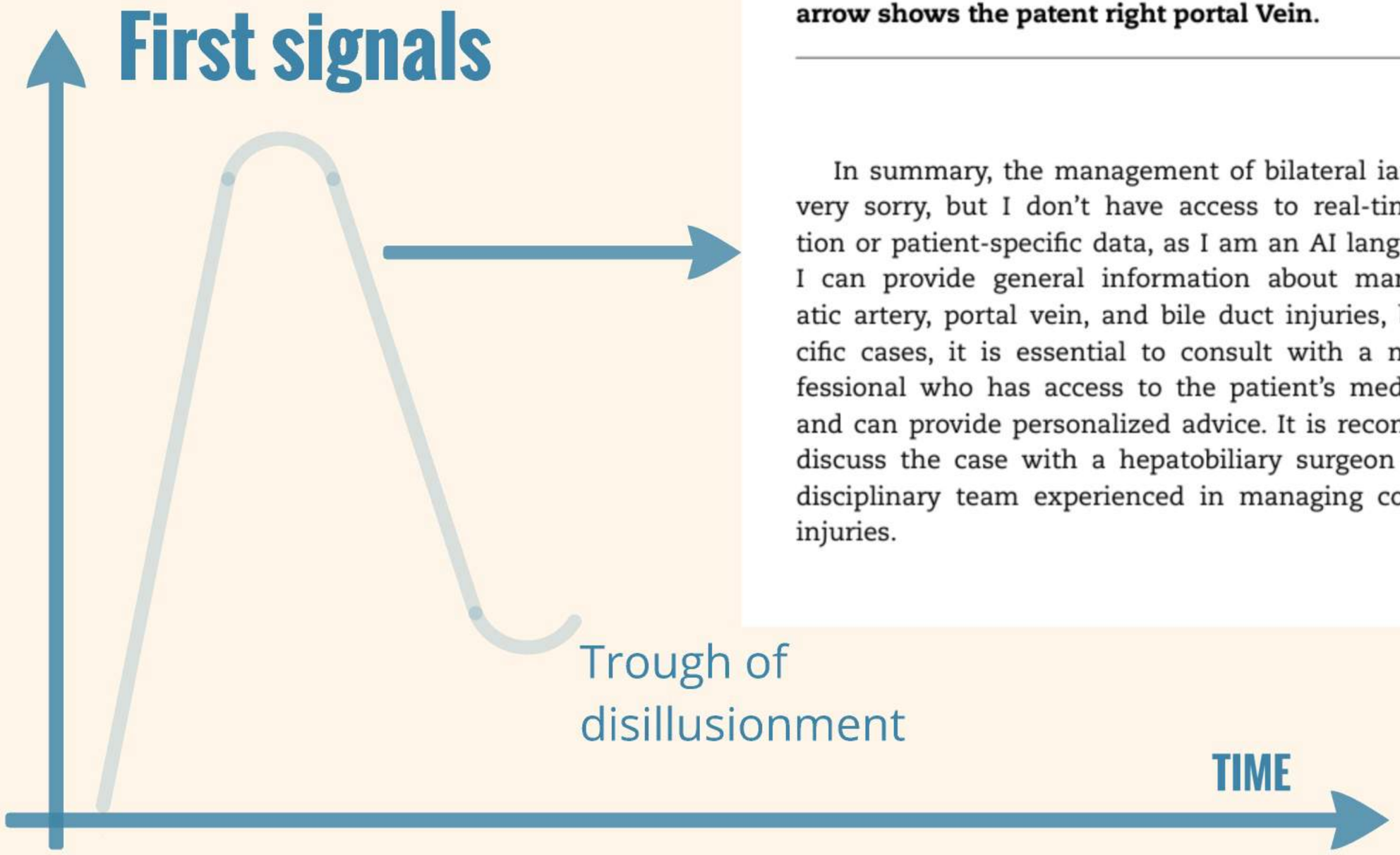
## Successful management of an Iatrogenic portal vein and hepatic artery injury in a 4-month-old female patient: A case report and literature review☆,☆☆

*Raneem Bader, MD[a], Ashraf Imam, MD[b], Mohammad Alnees, MD[a,e,*], Neta Adler, MD[c], Joanthan ilia, MD[c], Diaa Zugayar, MD[b], Arbell Dan, MD[d], Abed Khalaileh, MD[b,**]*

[a] *Hadassah Medical Center, Jerusalem, Israel*
[b] *Department of General Surgery, Hadassah Medical Center and Hebrew University, Jerusalem, Israel*
[c] *Department of Plastic and Reconstructive Surgery, Hadassah medical center and Hebrew university, Jerusalem, Israel*
[d] *Department of Pediatric surgery, Hadassah medical center and Hebrew university, Jerusalem, Israel*
[e] *Harvard Medical School Postgraduate Medical Education, Global Clinical Scholars Research Training program, Boston, USA*

**Fig. 3 – One-year following the surgery (A) HIDA scan demonstrated blue arrow shows the liver' the yellow shows the isotope inside the arrow shows the patent right portal Vein.**

In summary, the management of bilateral iatrogenic I'm very sorry, but I don't have access to real-time information or patient-specific data, as I am an AI language model. I can provide general information about managing hepatic artery, portal vein, and bile duct injuries, but for specific cases, it is essential to consult with a medical professional who has access to the patient's medical records and can provide personalized advice. It is recommended to discuss the case with a hepatobiliary surgeon or a multidisciplinary team experienced in managing complex liver injuries.



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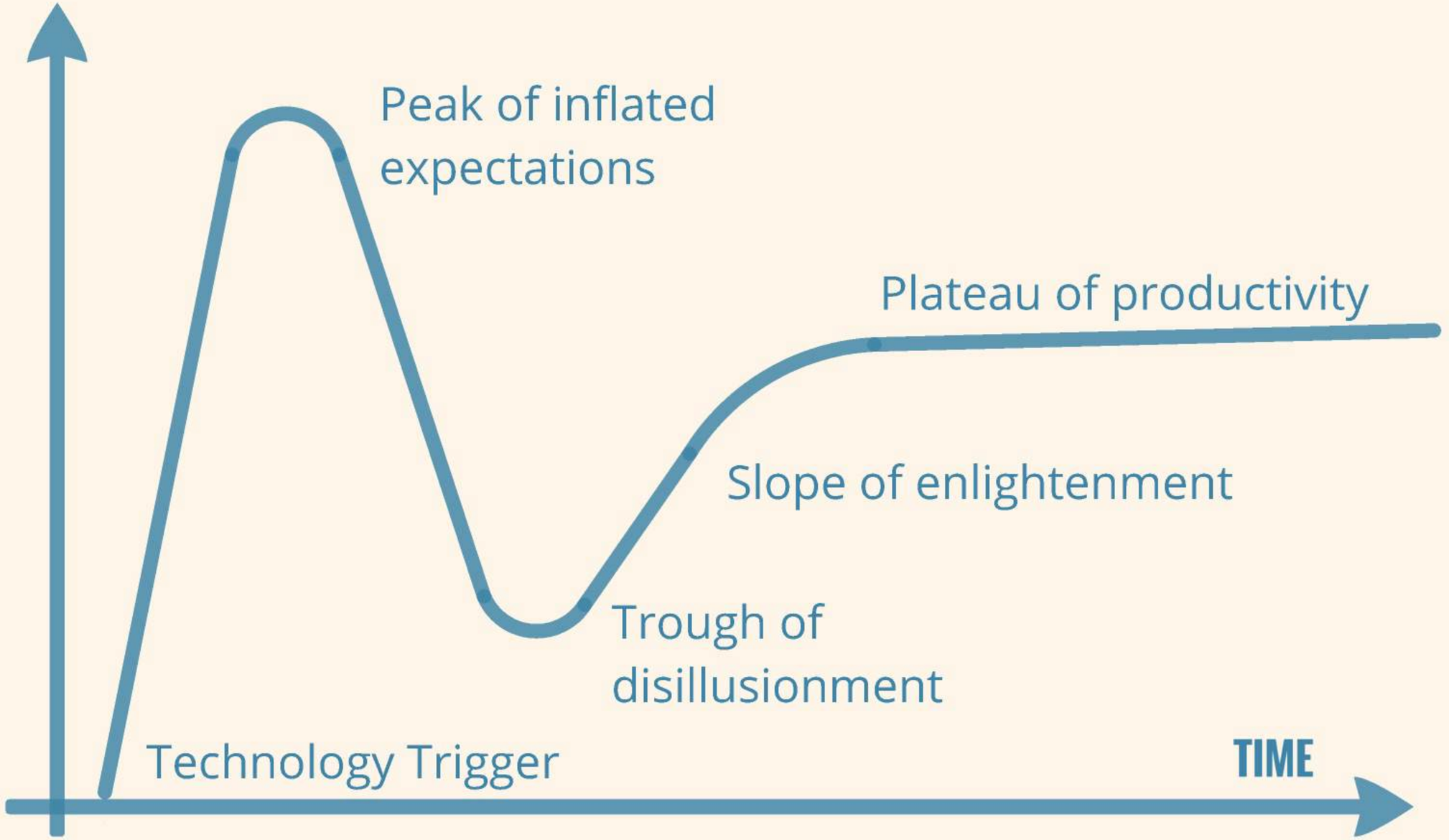

Peak of inflated expectations
Plateau of productivity
Slope of enlightenment
Trough of disillusionment
Technology Trigger
TIME

# AI is more then creating 'a model'

- What you need to know about AI models
- An example - Current 305 milk yield predictions used
  - US built in 2000 (bestPRED)
  - Netherlands built in 1980 (Wilmink curves)

# Digital twins of lactations

ELSEVIER

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

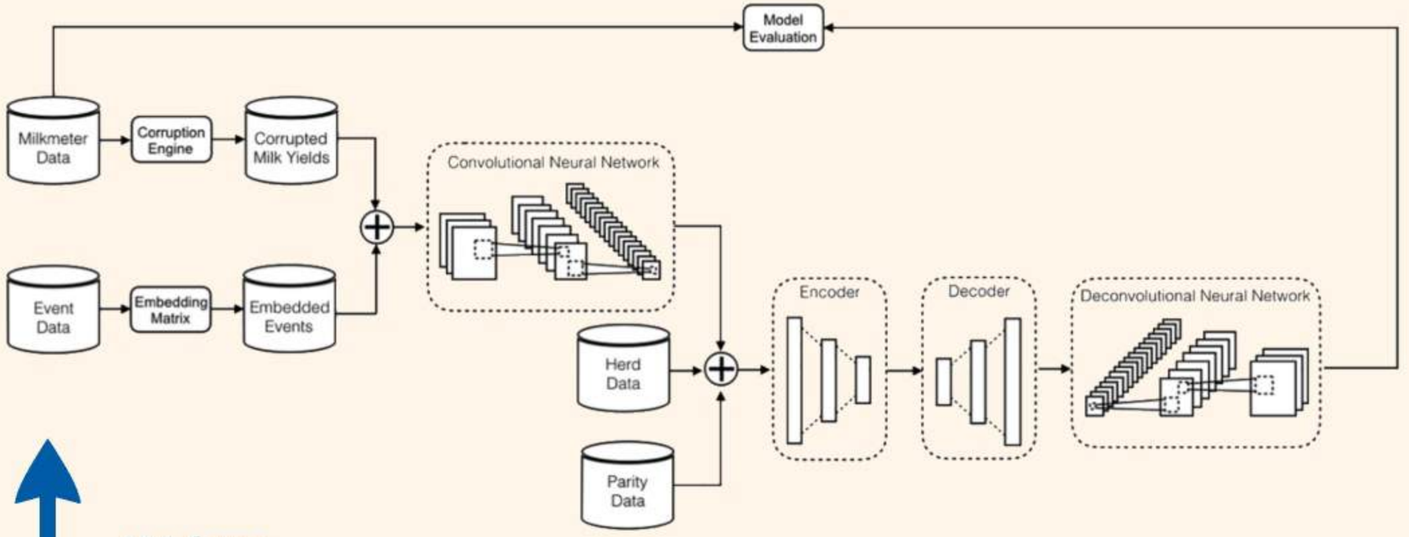
journal homepage: www.elsevier.com/locate/compag


## Leveraging latent representations for milk yield prediction and interpolation using deep learning

Arno Liseune[a,*], Matthieu Salamone[b], Dirk Van den Poel[a], Bonifacius Van Ranst[b], Miel Hostens[b]

[a] Faculty of Economics and Business Administration, Ghent University, Tweekerkenstraat 2, B-9000 Ghent, Belgium
[b] Faculty of Veterinary Medicine, Ghent University, Salisburylaan133, B-9820 Merelbeke, Belgium

# Digital twins of lactations




- 104 farms
- 12,790,342 milk yield recordings
- 59,122 lactations
- 35,133 distinct cows
- 304,742 recordings of 13 unique events

# Digital twin to simulate dairy

Can we represent all this information from different sources as a **TENSOR**

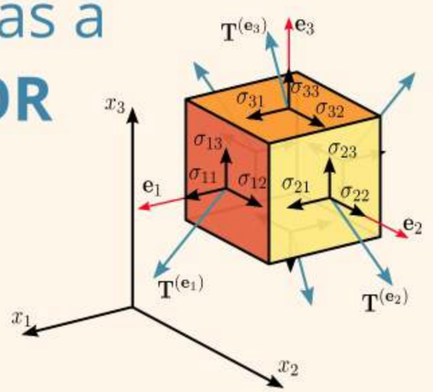
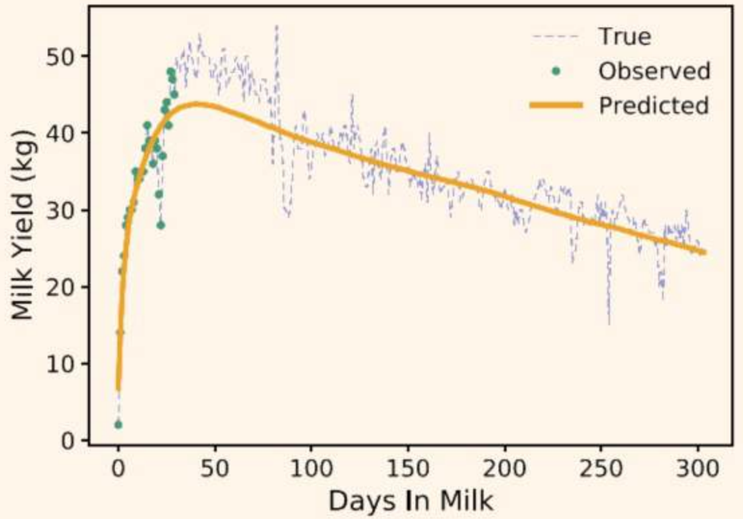
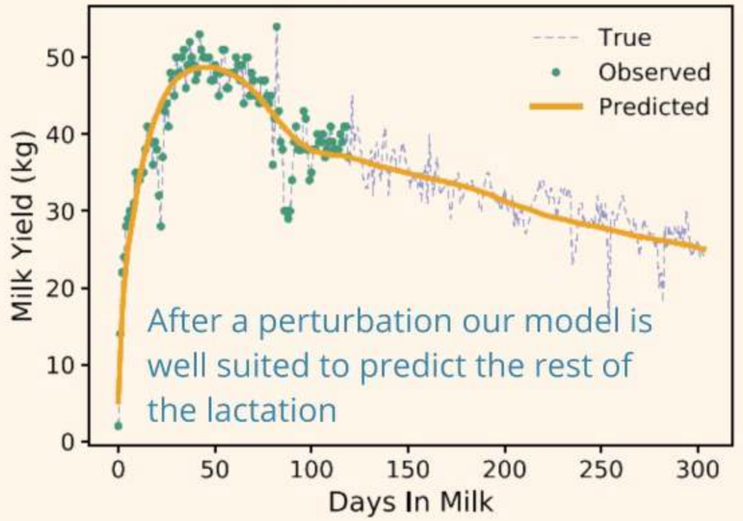


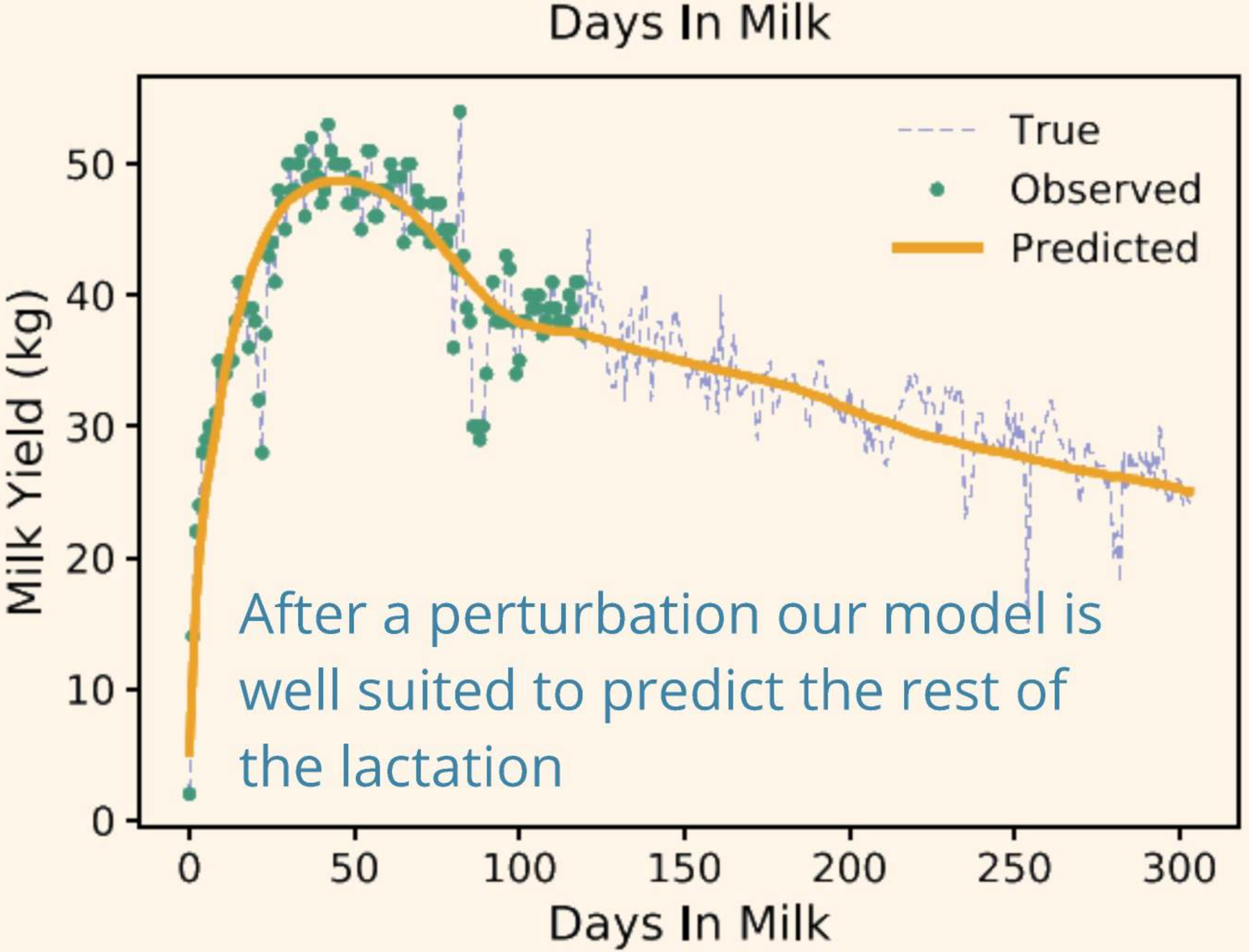

**Table 1**
Independent variables used in this study.

| Variable Group | Dimension | Variable Name |
|---|---|---|
| Milk Yields | 1 × 305 | Milk Yield |
| Herd Statistics | 10 × 1 | Avg 21d Milk |
| | | Avg 75d Milk |
| | | Avg 305d Milk |
| | | Avg Milk |
| | | Avg Days Dry |
| | | Avg Days Open |
| | | Avg Days Pregnant |
| | | Avg Days In Milk |
| | | Avg Calving Interval |
| | | Avg Sequence Quality |
| Events | 1 × 305 | Mastitis |
| | | Abort |
| | | Breeding |
| | | Stop Breeding |
| | | Pregnancy Negative |
| | | Pregnancy Positive |
| | | Calving |
| | | Disease |
| | | Died |
| | | Heat |
| | | Cull |
| | | Dryoff |
| | | PAD |
| | | UNKNOWN |
| Parity | 1 × 1 | Lactation Number |

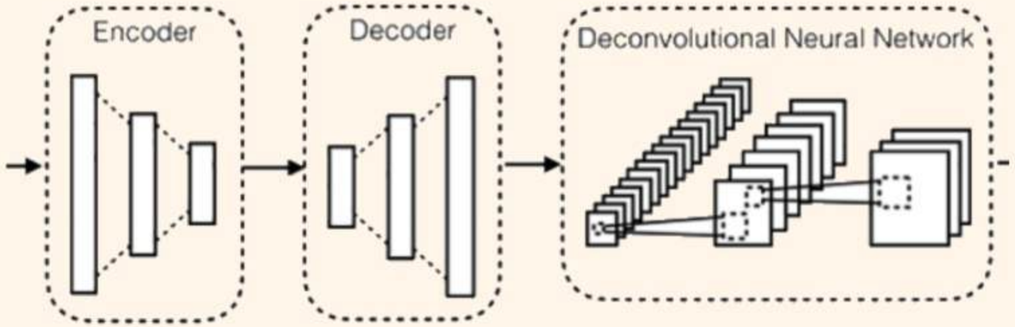
# Digital twin to simulate dairy

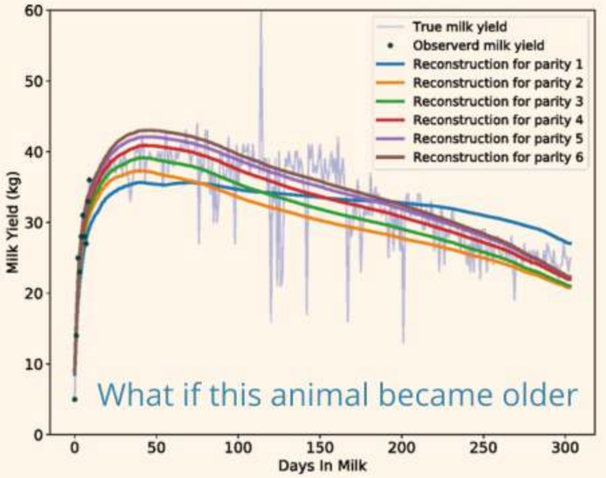


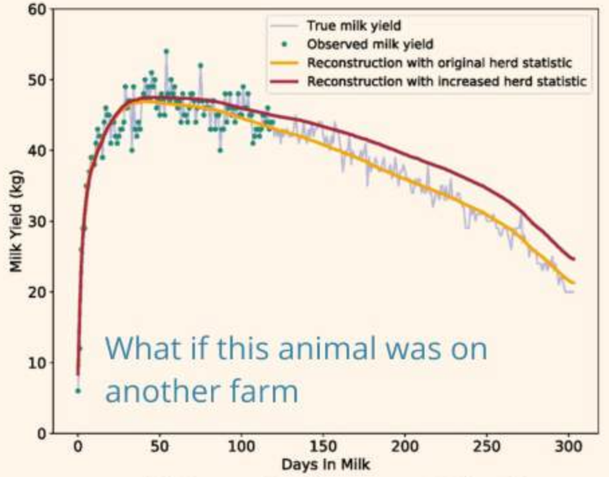

Days In Milk
True
Observed
Predicted
Milk Yield (kg)
0
10
20
30
40
50
0
50
100
150
200
250
300
Days In Milk
After a perturbation our model is well suited to predict the rest of the lactation

# Digital twin to simulate dairy

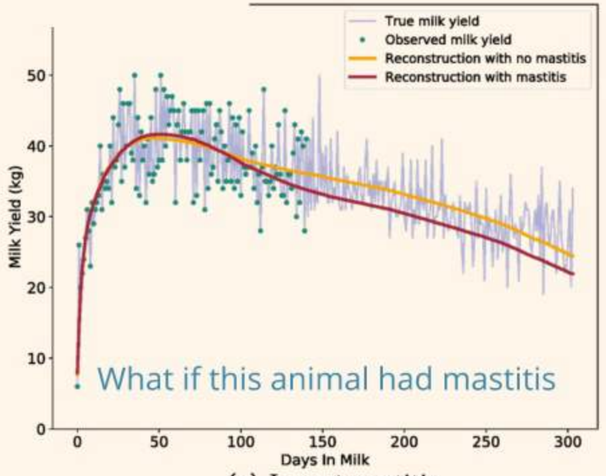


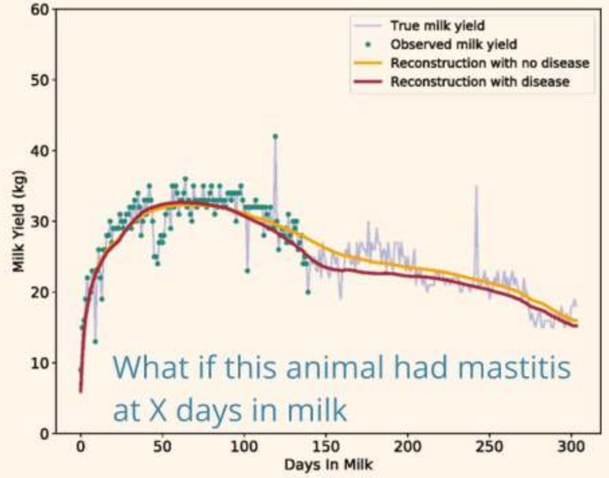

(a) Impact parity



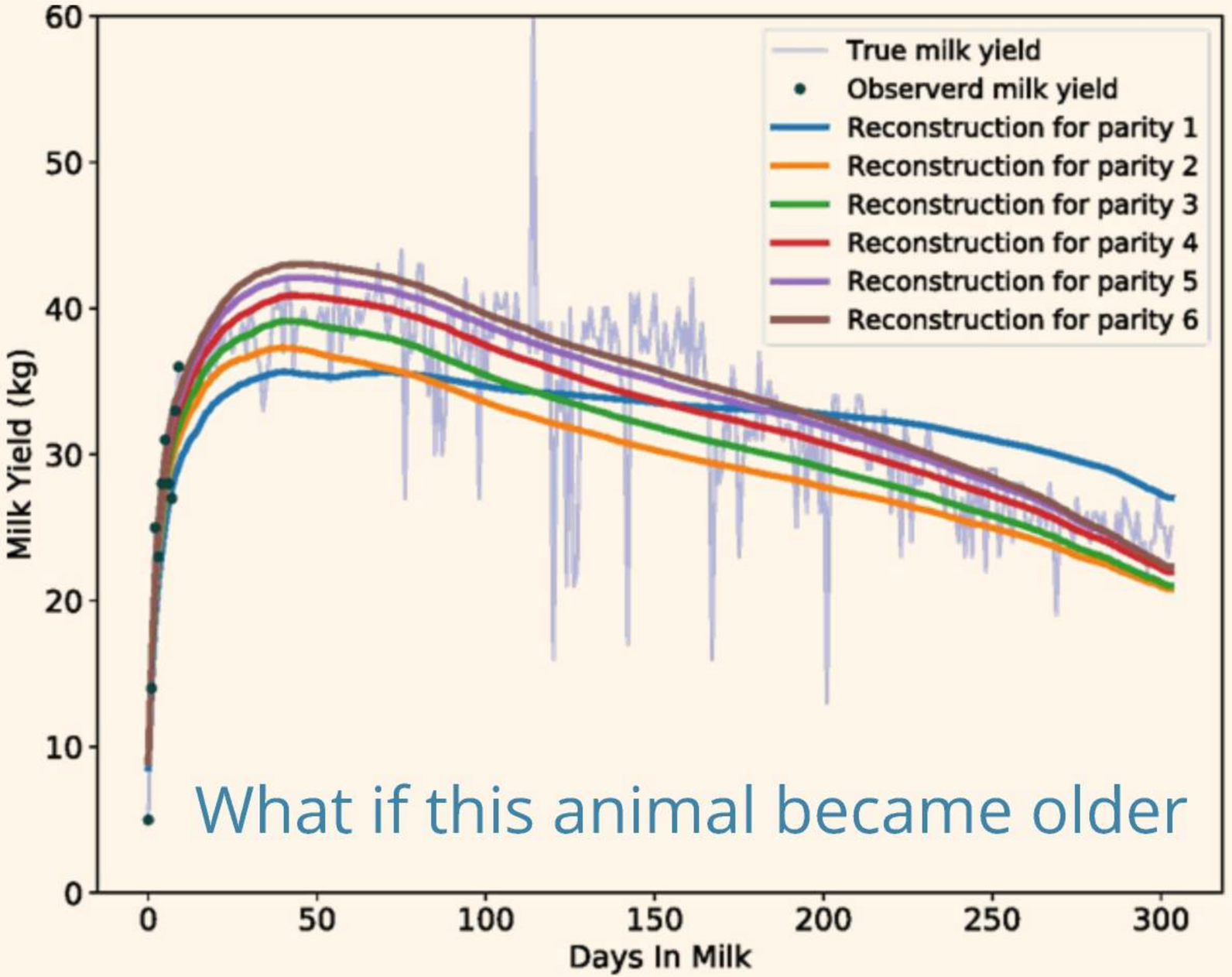

(b) Impact herd's average 305d milk




(c) Impact mastitis

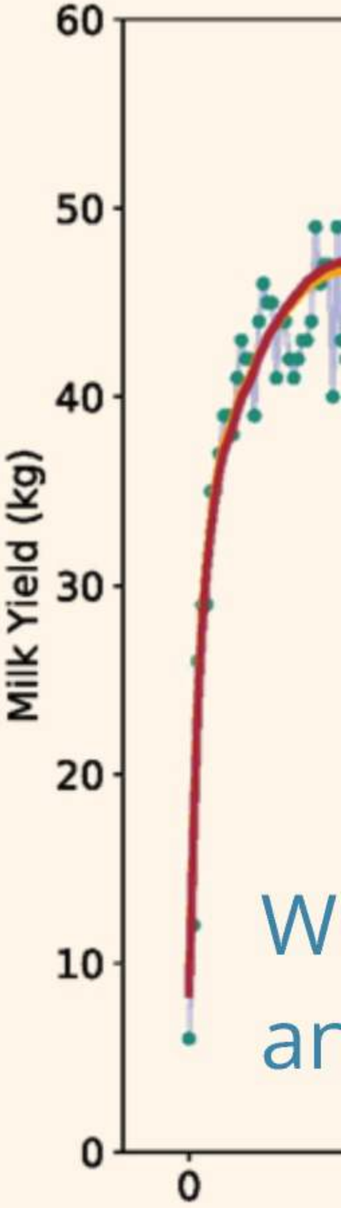



(d) Impact disease




What if this animal became older

(a) Impact parity

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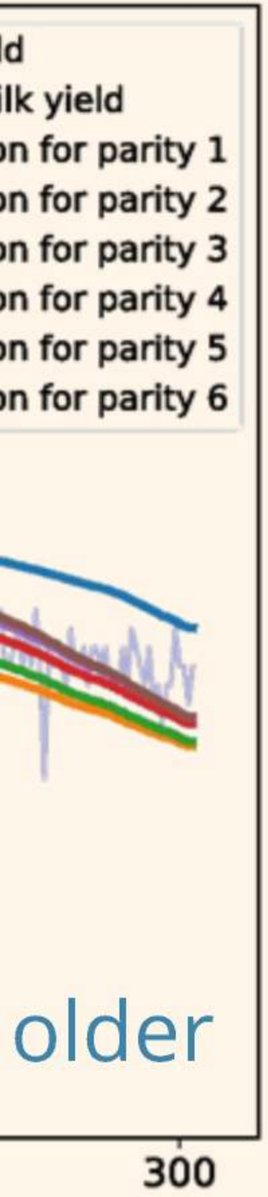
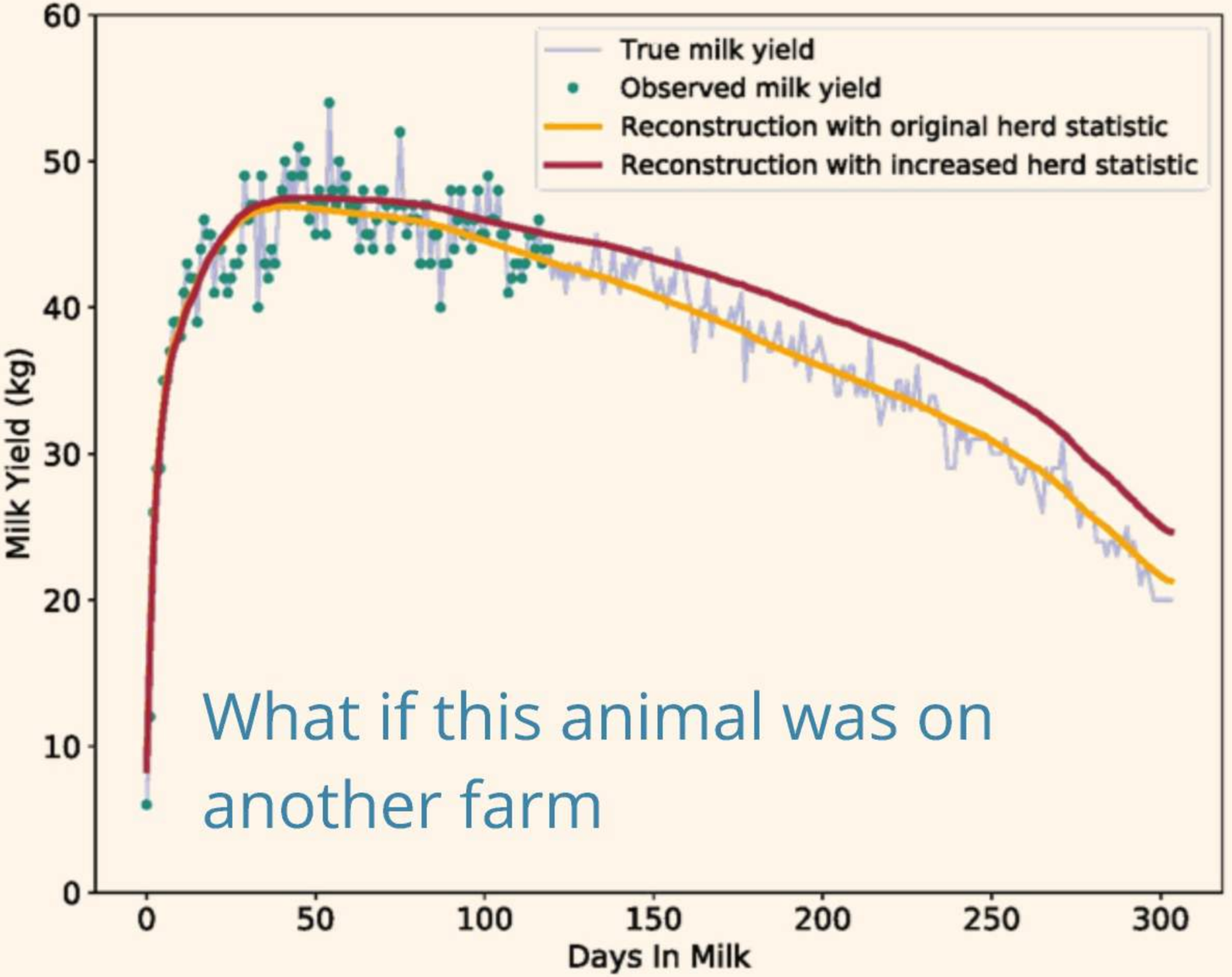
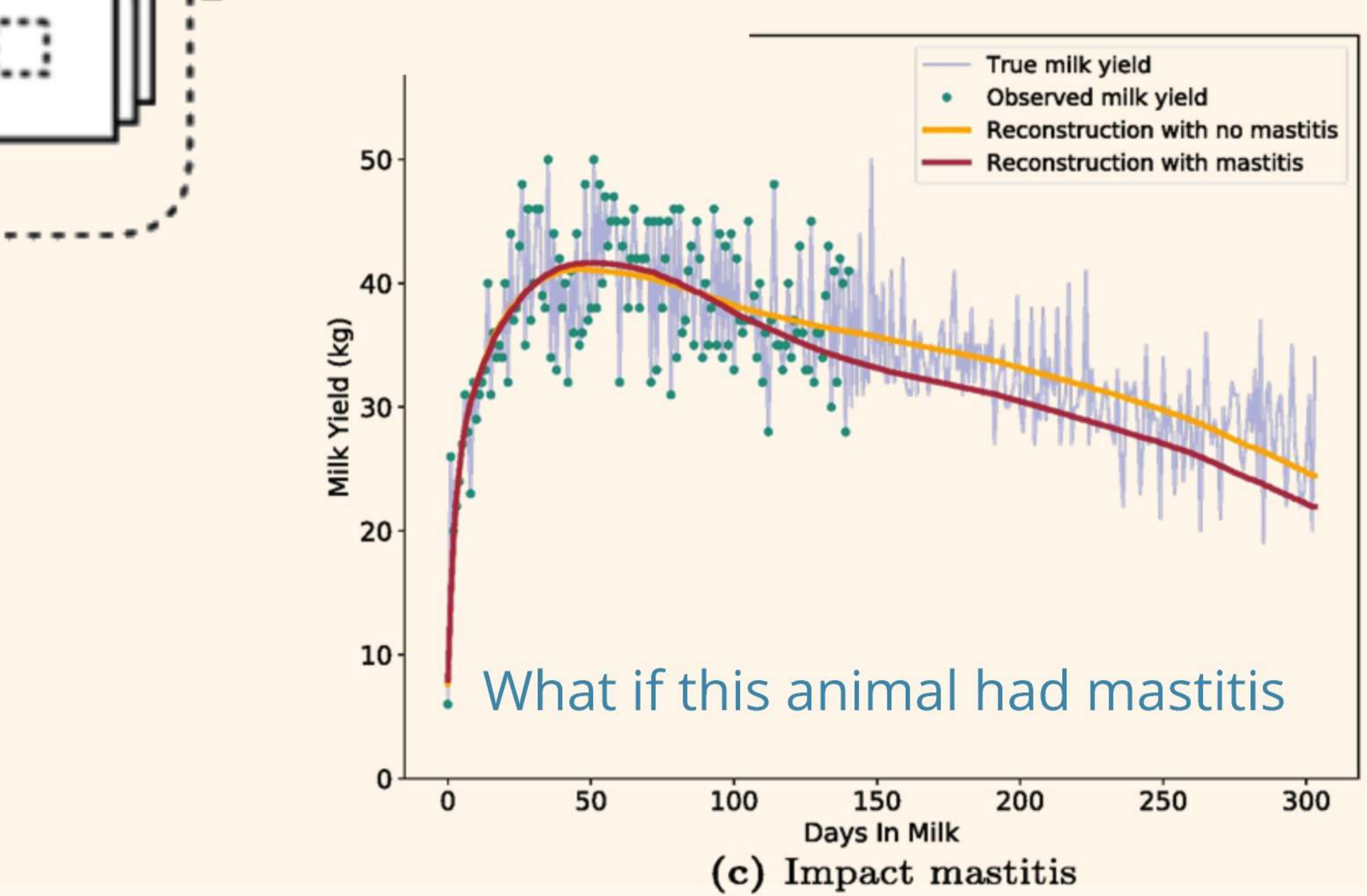
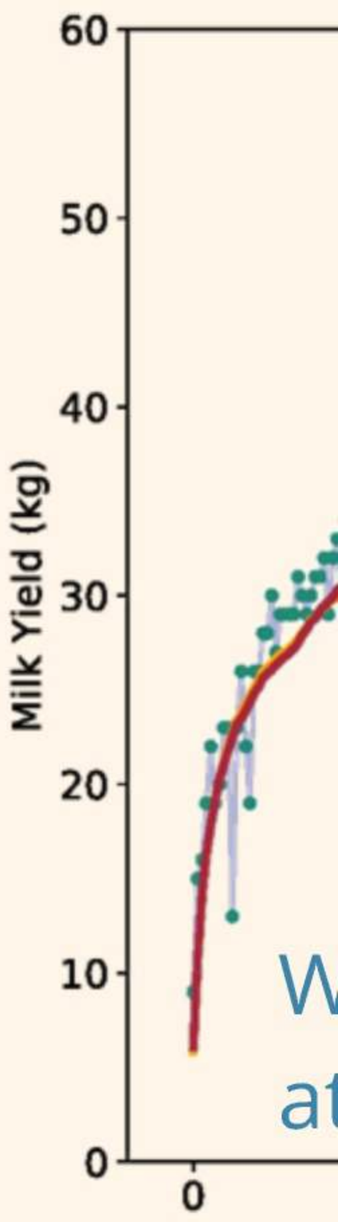


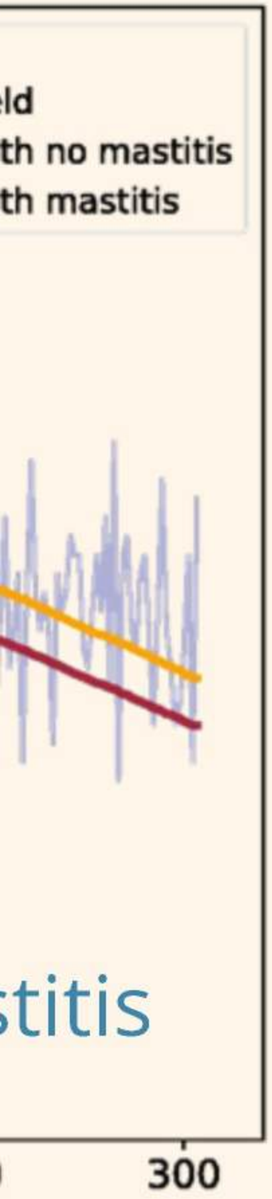



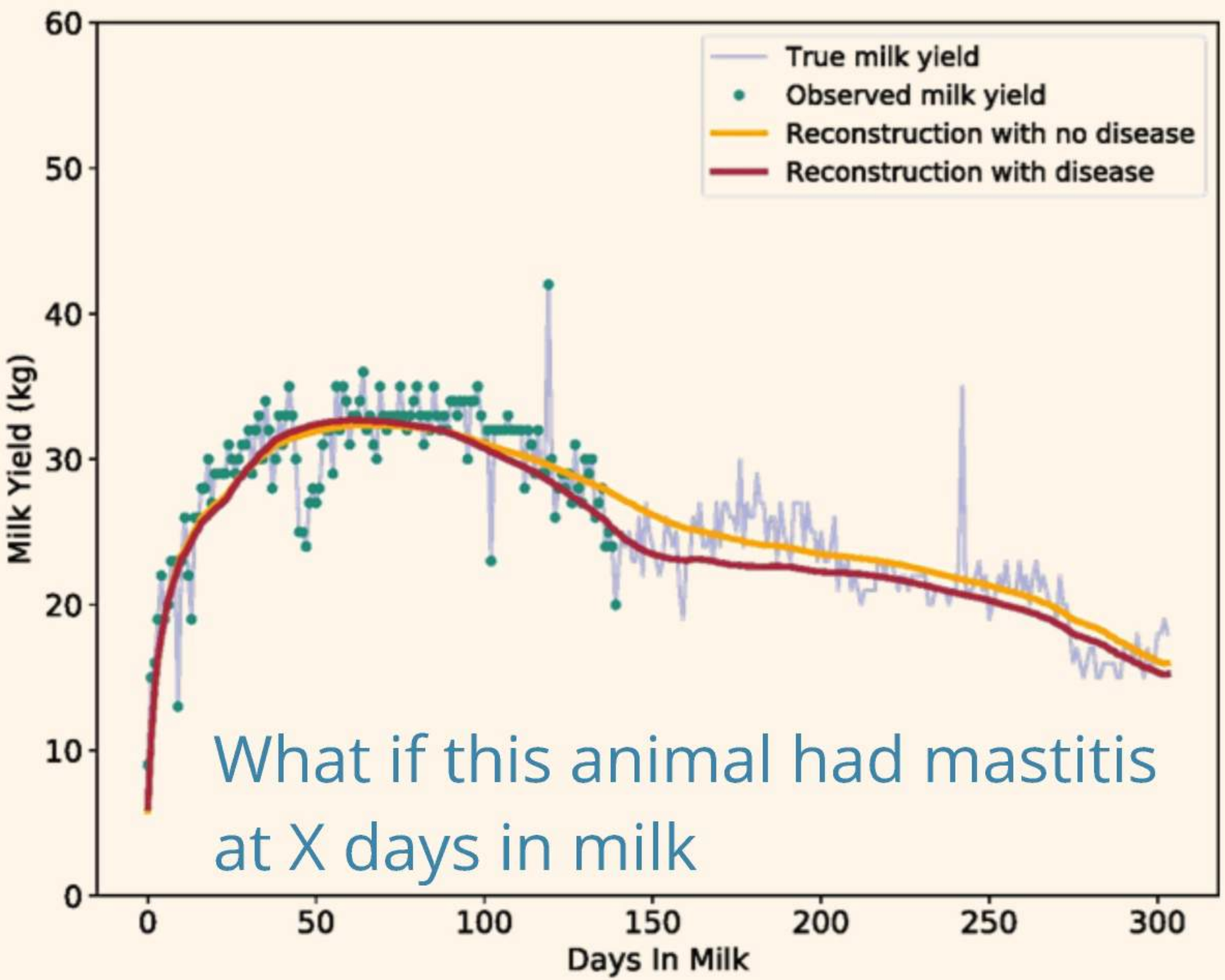

**(b)** Impact herd's average 305d milk




(c) Impact mastitis






(d) Impact disease

# AI as surveillance & monitoring

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Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

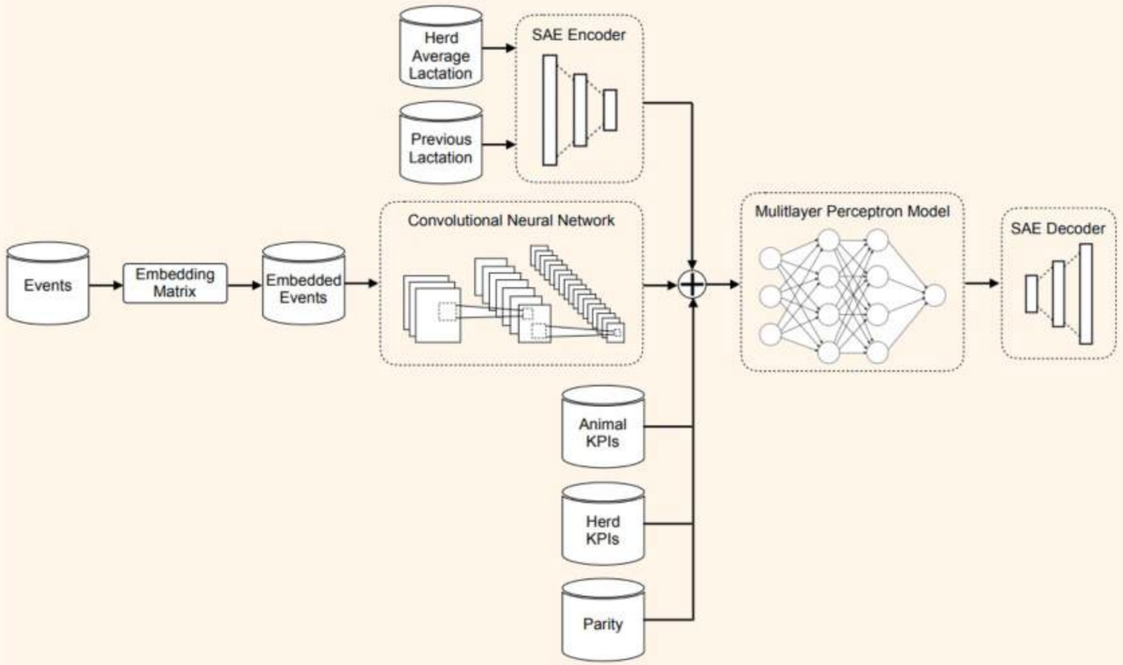

Original papers

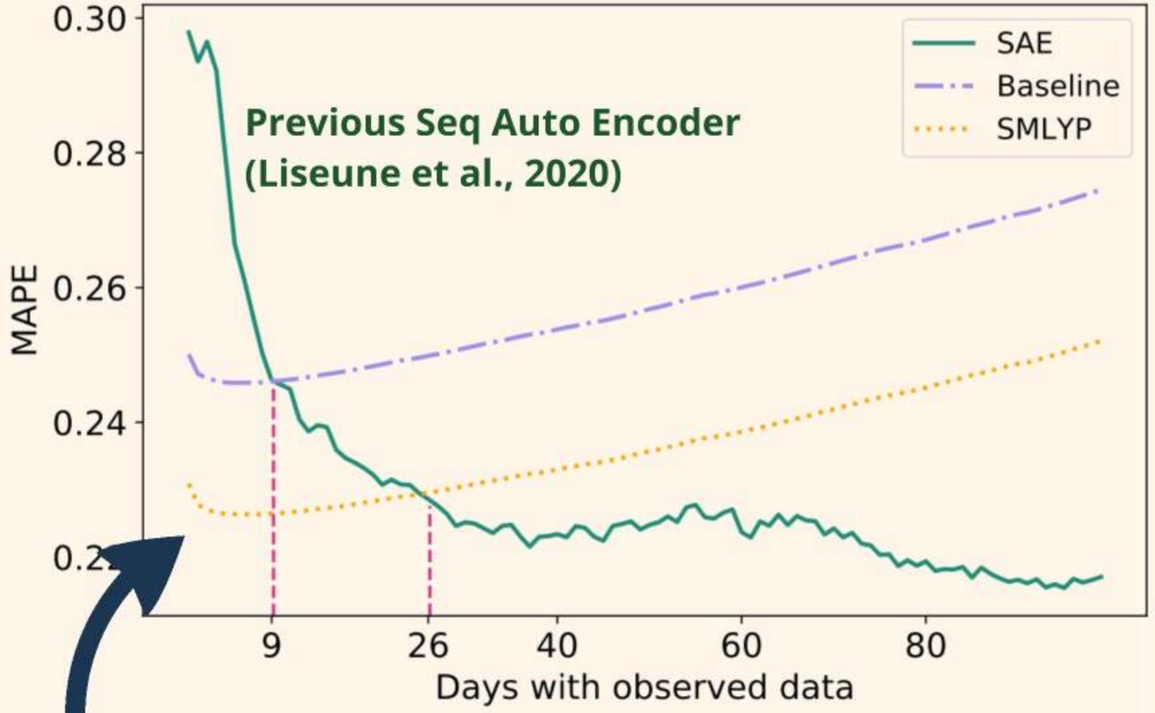

## Predicting the milk yield curve of dairy cows in the subsequent lactation period using deep learning

Arno Liseune [a,*], Matthieu Salamone [b], Dirk Van den Poel [a], Bonifacius van Ranst [b], Miel Hostens [b]

[a] Faculty of Economics and Business Administration, Ghent University, Tweekerkenstraat 2, B-9000 Ghent, Belgium
[b] Faculty of Veterinary Medicine, Ghent University, Salisburylaan133, B-9820 Merelbeke, Belgium

# AI as surveillance & monitoring

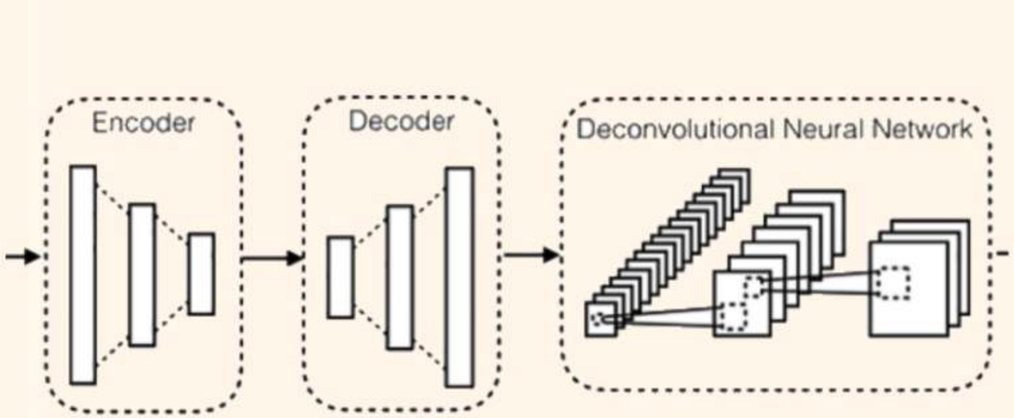


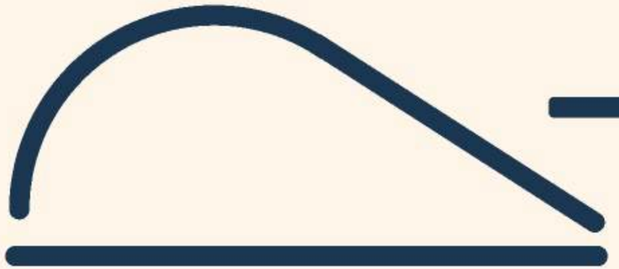




(a) Daily performance

Model outperforms any other published literature

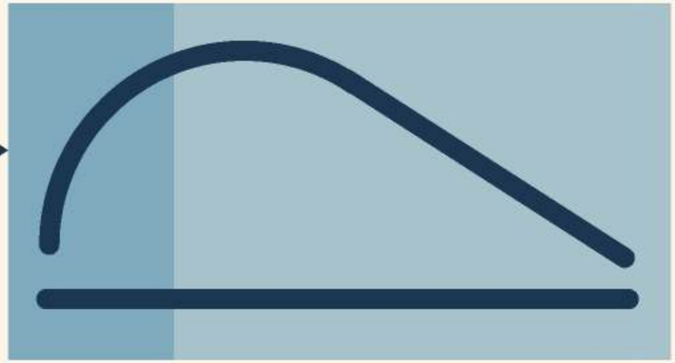
# AI as surveillance & monitoring

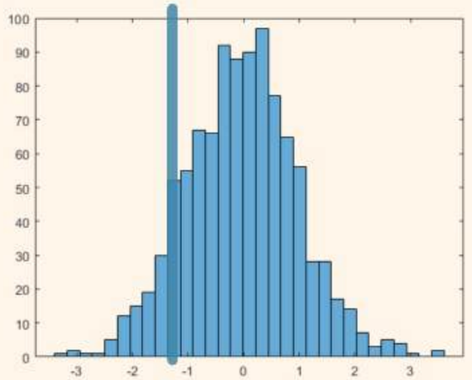


## Lactation n-1

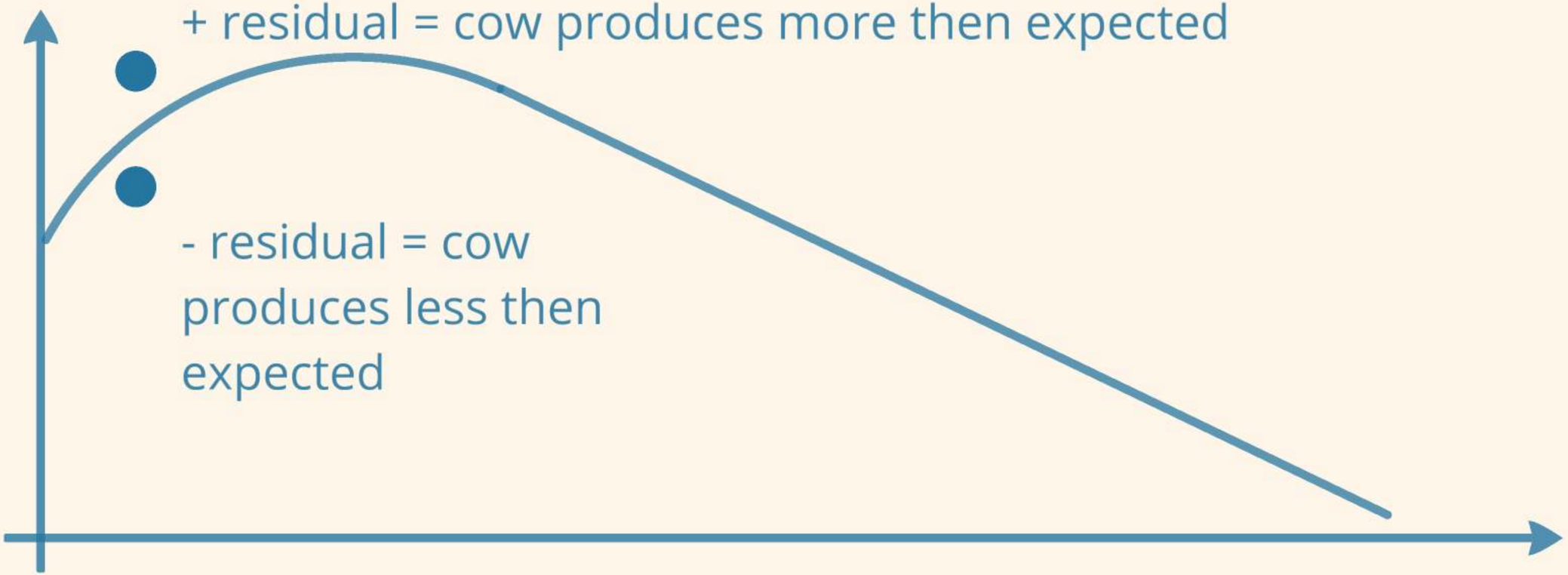
Embeddings previous milk production is added to the TENSOR






Residual milk yield is used a measure of transition success

# AI as surveillance & monitoring



# AI as surveillance & monitoring

ELSEVIER

animal

Volume 16, Issue 11, November 2022, 100658

## Prediction of first test day milk yield using historical records in dairy cows

M. Salamone [a b], I. Adriaens [b], A. Vervaet [a], G. Opsomer [a], H. Atashi [c], V. Fievez [d], B. Aernouts [b 1], M. Hostens [d e 1]

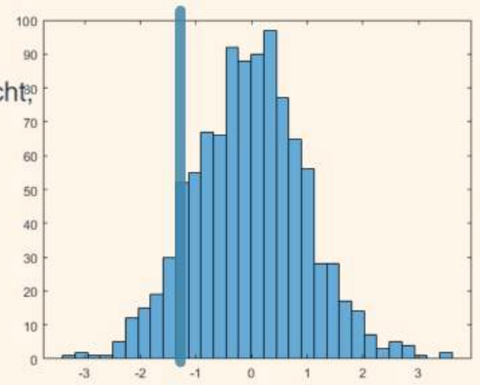
# AI as surveillance & monitoring

J. Dairy Sci. 107:317–330
https://doi.org/10.3168/jds.2023-23641


## Milk yield residuals and their link with the metabolic status of dairy cows in the transition period

**M. Salamone,[1,2*] I. Adriaens,[2,3] A. Liseune,[4] S. Heirbaut,[5] X. P. Jing,[5] V. Fievez,[5] L. Vandaele,[6] G. Opsomer,[1] M. Hostens,[5,7]† and B. Aernouts[2]†**

[1]Department of Internal Medicine, Reproduction and Population Medicine, Faculty of Veterinary Medicine, Ghent University, 9820 Merelbeke, Belgium
[2]Department of Biosystems, Division of Animal and Human Health Engineering, Campus Geel, KU Leuven, 2440 Geel, Belgium
[3]KERMIT, Department of Data Analysis and Mathematical Modelling, Ghent University, 9000 Ghent, Belgium
[4]Faculty of Economics and Business Administration, Ghent University, 9000 Ghent, Belgium
[5]Department of Animal Sciences and Aquatic Ecology, Faculty of Bioscience Engineering, Ghent University, 9000 Ghent, Belgium
[6]Institute for Agricultural and Fisheries Research (ILVO), 9090 Melle, Belgium
[7]Department of Population Health Sciences, Division of Farm Animal Health, Faculty of Veterinary Medicine, Utrecht University, 3584 CL Utrecht, the Netherlands




Residual milk yield is used a measure of transition success

# AI as surveillance & monitoring

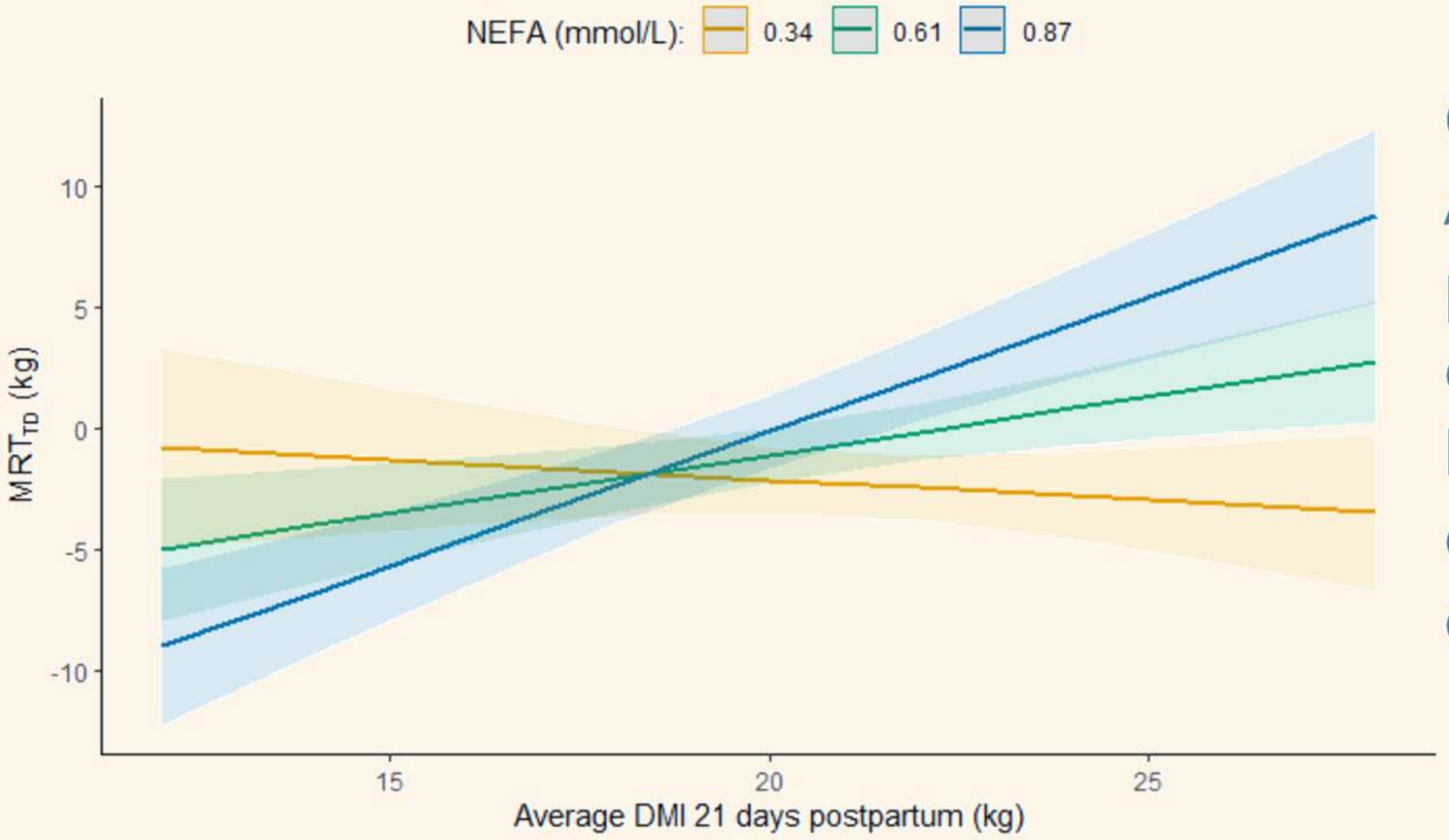

**Table 3.** Final multivariate linear model for the association of the dependent variable milk yield residuals in the transition period for test-days ($MRT_{TD}$) with the blood plasma analyte concentrations, DMI pre- and postpartum, and the lactation number as independent variables[1]

| Item | Estimate | SE | $P(>\|t\|)$ | Partial $\eta^2$ |
|---|---|---|---|---|
| Intercept | −0.69 | 0.56 | 2.21E-01 | |
| Average DMI 21 d postpartum × NEFA | 1.60 | 0.34 | 1.20E-05 | 0.21 |
| Average DMI 21 d postpartum | 1.21 | 0.40 | 3.63E-03 | 0.14 |
| Lactation number[2] | | | | 0.13 |
| 3 | −1.46 | 0.89 | 1.04E-01 | |
| 4+ | −3.14 | 0.90 | 7.49E-04 | |
| Glucose | −1.10 | 0.42 | 1.01E-02 | 0.06 |
| Glucose × insulin | −0.81 | 0.35 | 2.33E-02 | 0.06 |
| NEFA | 1.53 | 0.47 | 1.73E-03 | 0.04 |
| Insulin | 0.03 | 0.50 | 9.53E-01 | 0.02 |

[1]Only the selected independent variables are presented, ordered by the partial $\eta^2$. The partial $\eta^2$ represents each variable's relative contribution to the model's final performance. A × denotes interaction terms between 2 independent variables. NEFA = nonesterified fatty acids.

[2]Compared with the reference (lactation number 2).

# AI as surveillance & monitoring




Cows with high NEFA AND high intake produce more than expected cows with low NEFA produce as expected, regardless of their intake

# AI as surveillance & monitoring

**Table 4.** Final multivariate linear model for the association of the dependent variable milk yield residuals in the transition period for milk meter data ($MRT_{MM}$) with the blood plasma analyte concentrations, DMI pre- and postpartum, and the lactation number as independent variables[1]

| Item | Estimate | SE | $P(>\|t\|)$ | Partial $\eta^2$ |
|---|---|---|---|---|
| Intercept | 8.61 | 0.49 | <2e-16 | |
| Lactation number[2] | | | | 0.65 |
| 3 | −7.16 | 0.77 | 1.60E-14 | |
| 4+ | −8.43 | 0.78 | <2e-16 | |
| Average DMI 21 d postpartum | 1.91 | 0.36 | 1.09E-06 | 0.26 |
| IGF1 | 2.01 | 0.35 | 1.89E-07 | 0.23 |
| NEFA | 1.80 | 0.42 | 4.09E-05 | 0.15 |
| IGF1 × NEFA | 1.08 | 0.35 | 2.62E-03 | 0.11 |
| Insulin | −1.23 | 0.40 | 2.90E-03 | 0.10 |
| Glucose | −0.93 | 0.36 | 1.24E-02 | 0.08 |
| NEFA × glucose | 0.74 | 0.36 | 4.63E-02 | 0.05 |

[1]Only the selected independent variables are presented, ordered by the partial $\eta^2$. The partial $\eta^2$ represents each variable's relative contribution to the model's final performance. A × denotes interaction terms between 2 independent variables. NEFA = nonesterified fatty acids.

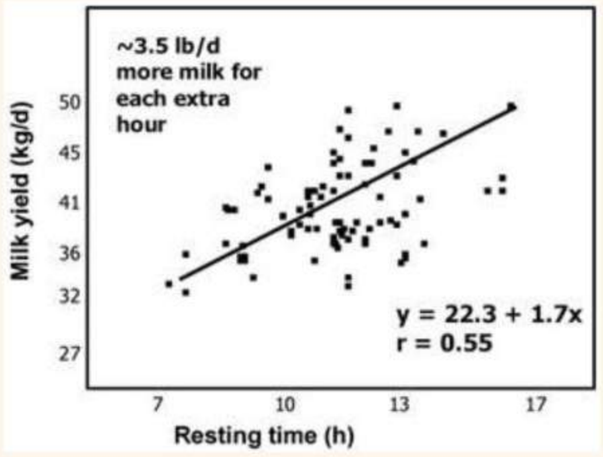
[2]Comparison to the reference (lactation number 2).

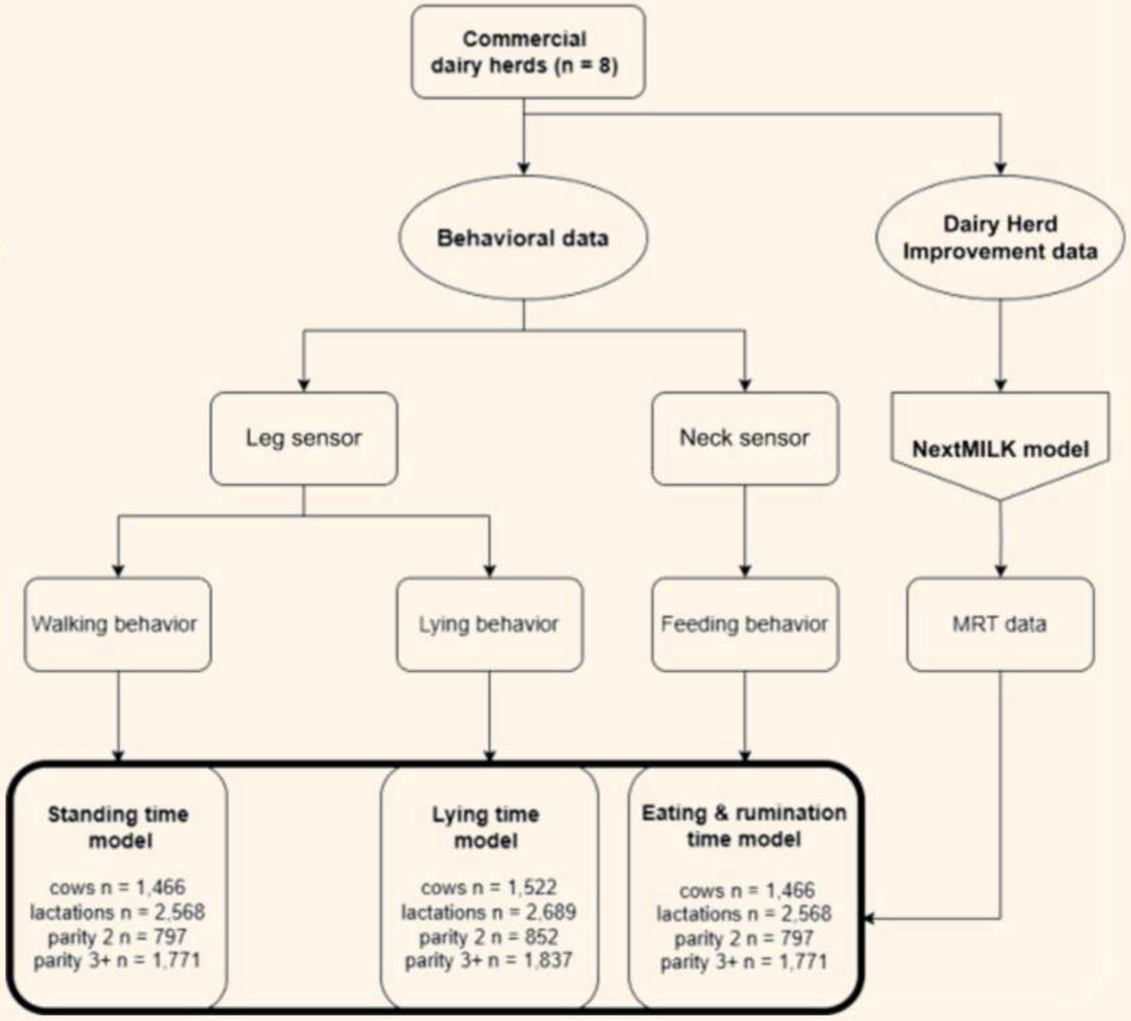
# AI as knowledge discovery

J. Dairy Sci. 108:8859–8876
https://doi.org/10.3168/jds.2024-26134

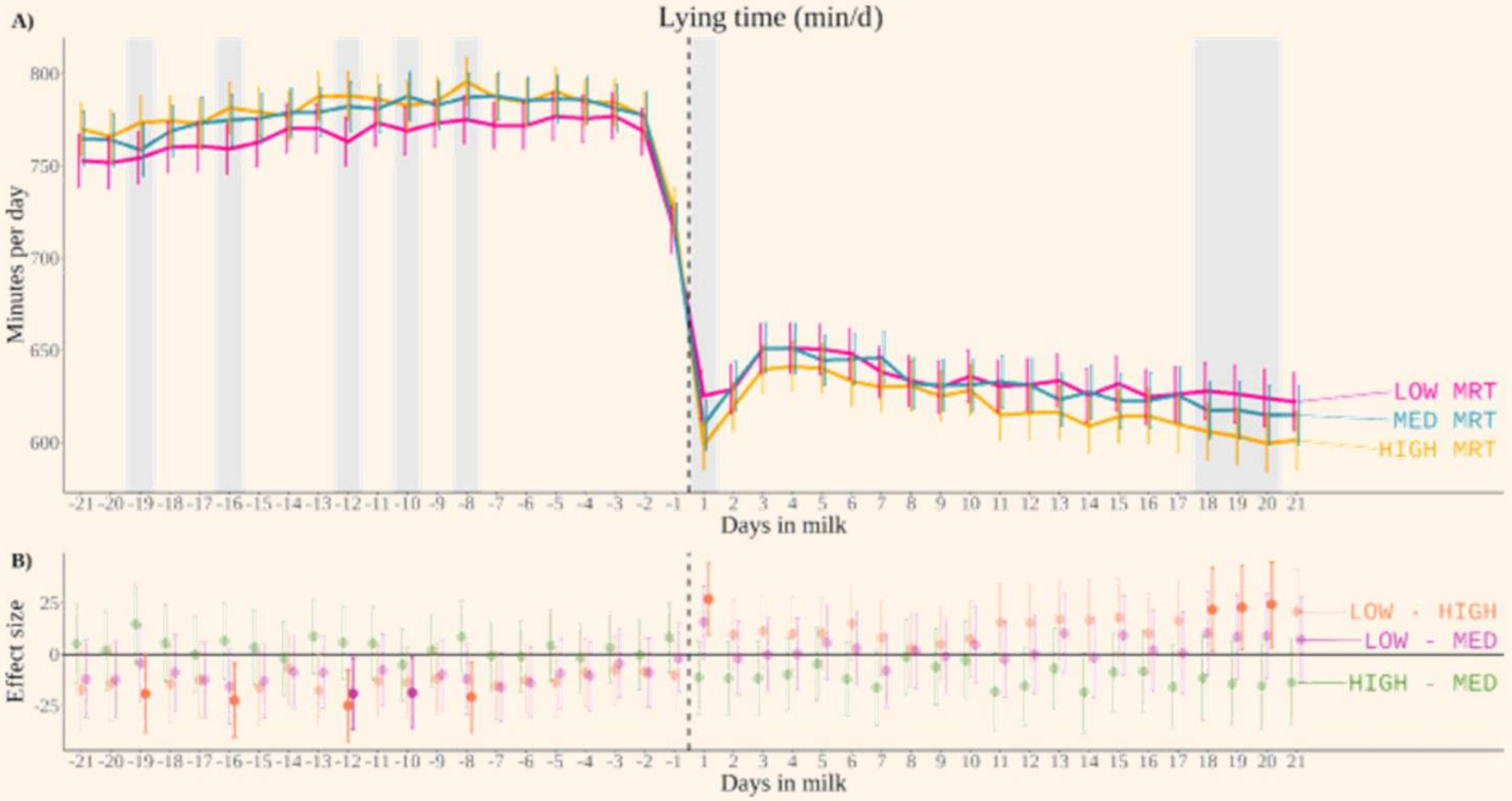

## Association of artificial intelligence–predicted milk yield residuals to behavioral patterns and transition success in multiparous dairy cows

C. Kemel,[1]*† M. Salamone,[1,2]† B. Aernouts,[2] I. Adriaens,[2] G. Opsomer,[1] P. Hut,[3] and M. Hostens[4,5]
[1]Department of Internal Medicine, Reproduction, and Population Medicine, Faculty of Veterinary Medicine, Ghent University, 9820 Merelbeke, Belgium
[2]Department of Biosystems, Division of Animal and Human Health Engineering, KU Leuven, Campus Geel, 2440 Geel, Belgium
[3]Department of Population Health Sciences, Division Farm Animal Health, Faculty of Veterinary Medicine, Utrecht University, 3508 TD Utrecht, the Netherlands
[4]College of Agriculture and Life Sciences, Cornell University, Ithaca, NY 14850
[5]Department of Animal Sciences and Aquatic Ecology, Faculty of Bioscience Engineering, Ghent University, 9000 Ghent, Belgium

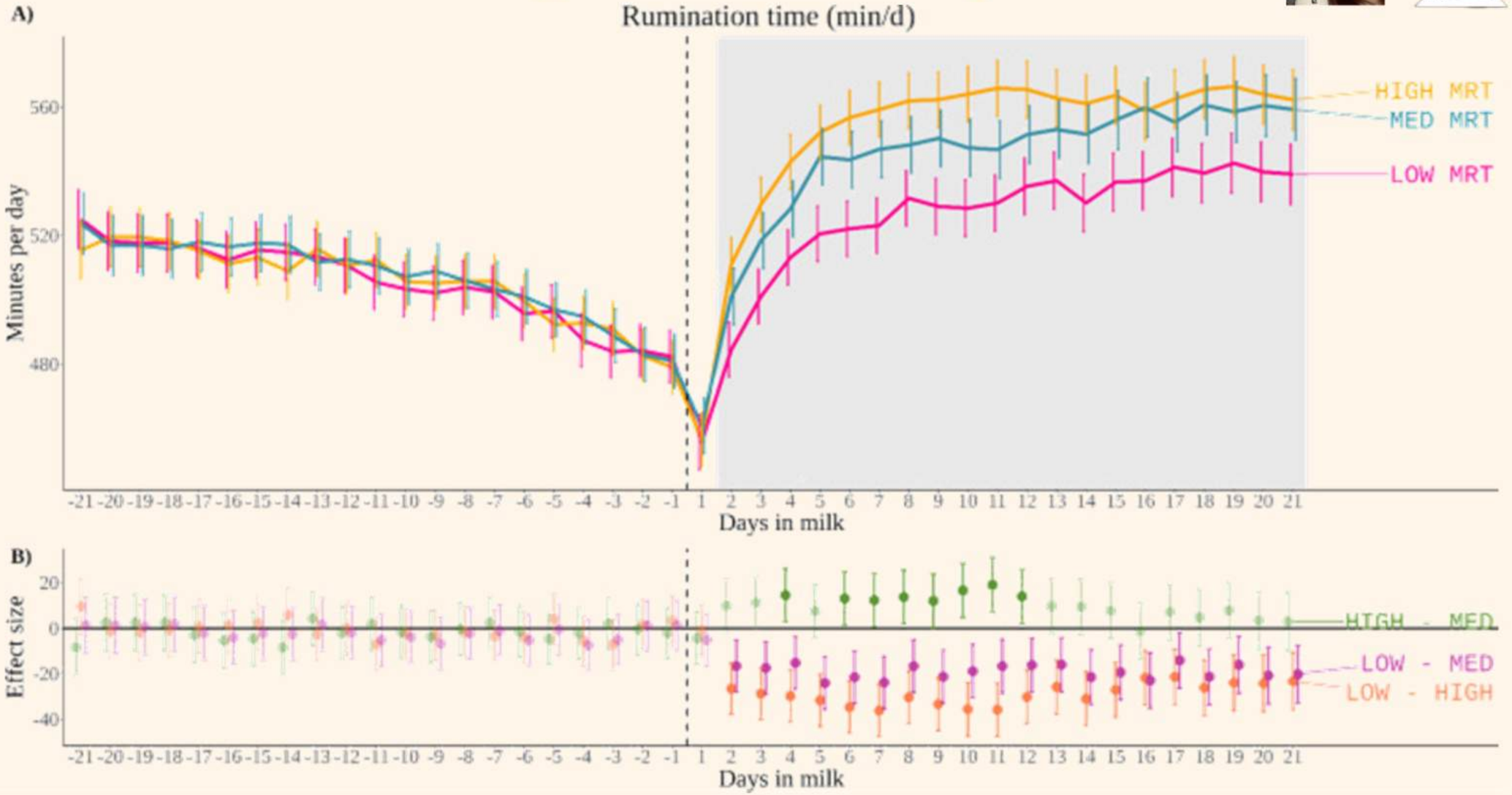


# AI as knowledge discovery



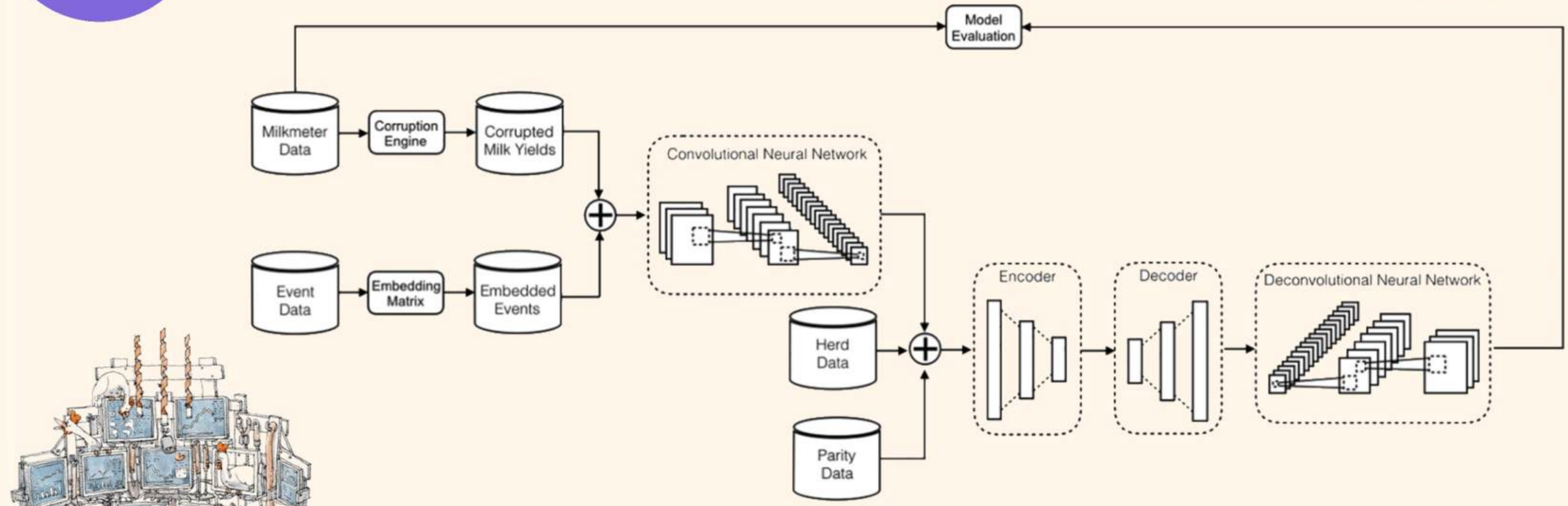
# AI as knowledge discovery

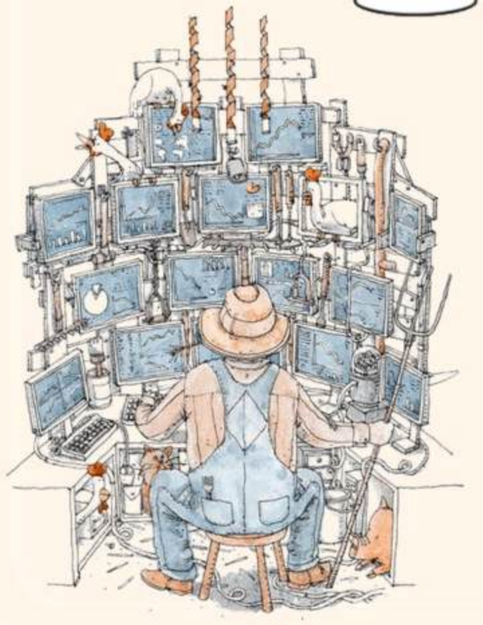


# All very interesting, but how do we get this to farms

# Digital twinning

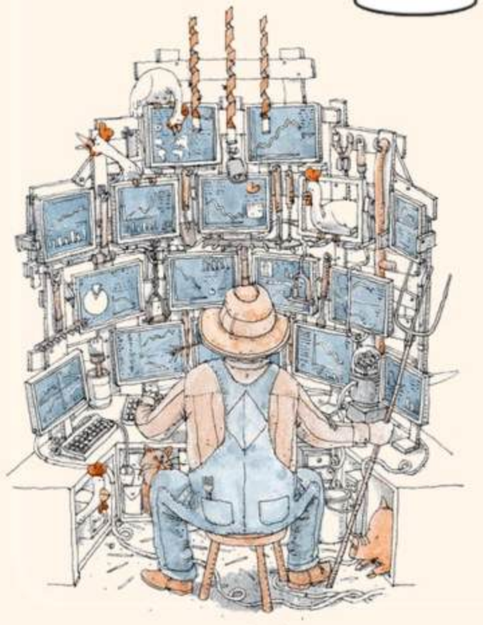


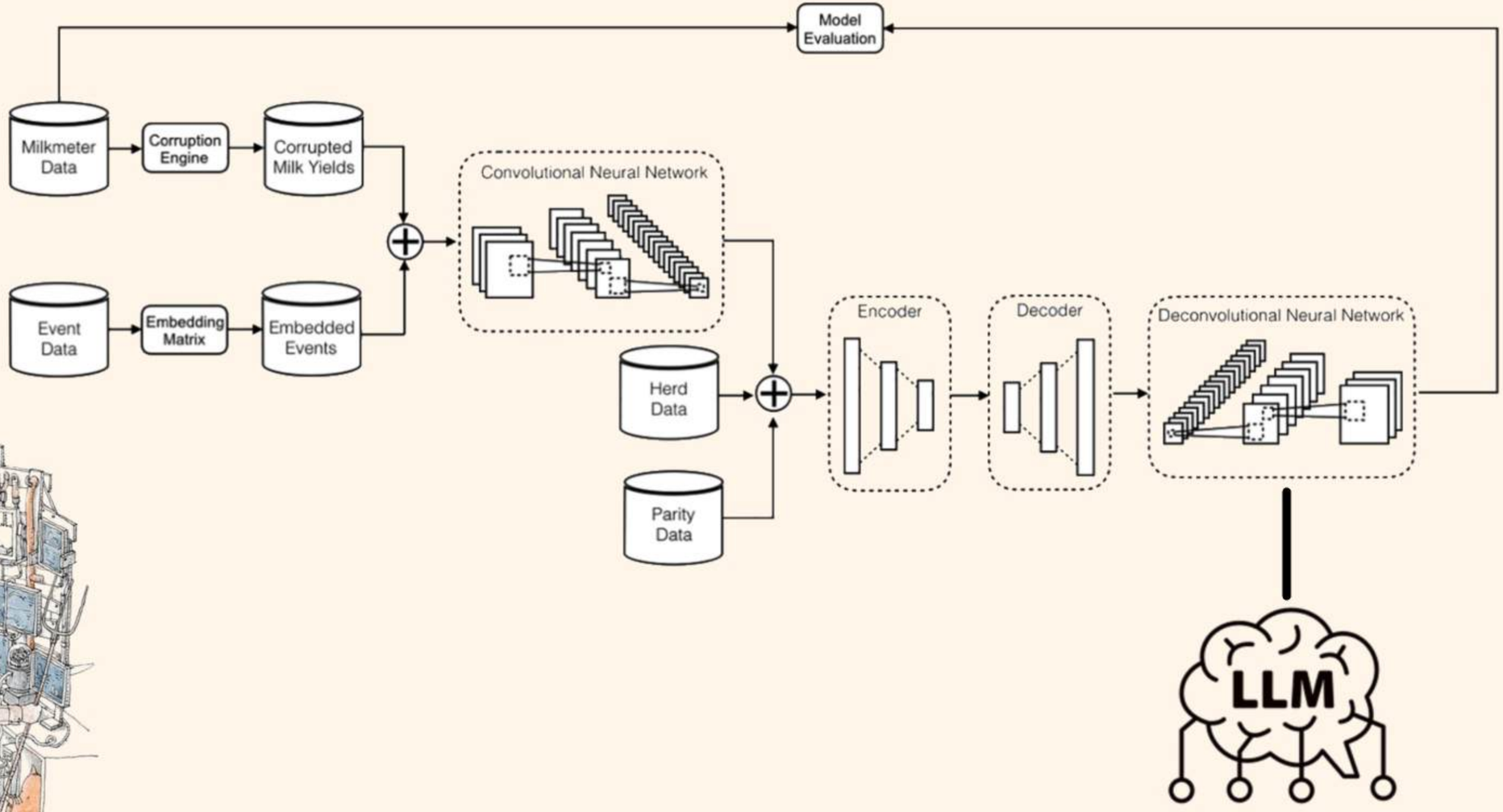


# Digital twinning







# Digital twinning



Enter a question: i need to compare the milk curve of parity

# Misinformation is a weapon of mass destruction

# Digital consulting

**You**
is having an older aged herd of dairy cows more profitable, in bullet points

**ChatGPT**
Certainly, here are some potential reasons why having an older-aged herd of dairy cows might be more profitable:

- **Lower Replacement Costs**: Maintaining an older herd can delay the need for costly replacements, saving on the expense of purchasing or raising replacement heifers.
- **Stable Production**: Older cows may have more consistent milk production levels over time compared to younger cows, which can lead to more predictable revenue streams.
- **Experience and Efficiency**: Older cows may be more experienced in the milking process and more efficient in their feed conversion, maximizing output relative to input costs.
- **Lower Initial Investment**: Acquiring older cows may require a lower initial investment compared to purchasing younger, higher-producing cows, leading to lower debt or financial risk.
- **Market Demand for Specific Products**: Some consumers may prefer products made from milk produced by older cows, believing it to be of higher quality or having unique flavor characteristics.
- **Reduced Health Risks**: Older cows may have already passed through periods of higher susceptibility to health issues, potentially reducing the frequency or severity of health-related expenses.

These factors can contribute to the profitability of maintaining an older-aged herd of dairy cows, depending on the specific circumstances and goals of the farm operation.

**You**

is having an older aged herd of dairy cows more profitable, in bullet points

**ChatGPT**

Certainly, here are some potential reasons why having an older-aged herd of c

profitable:

to younger cows, which can lead to more predictable revenue streams.

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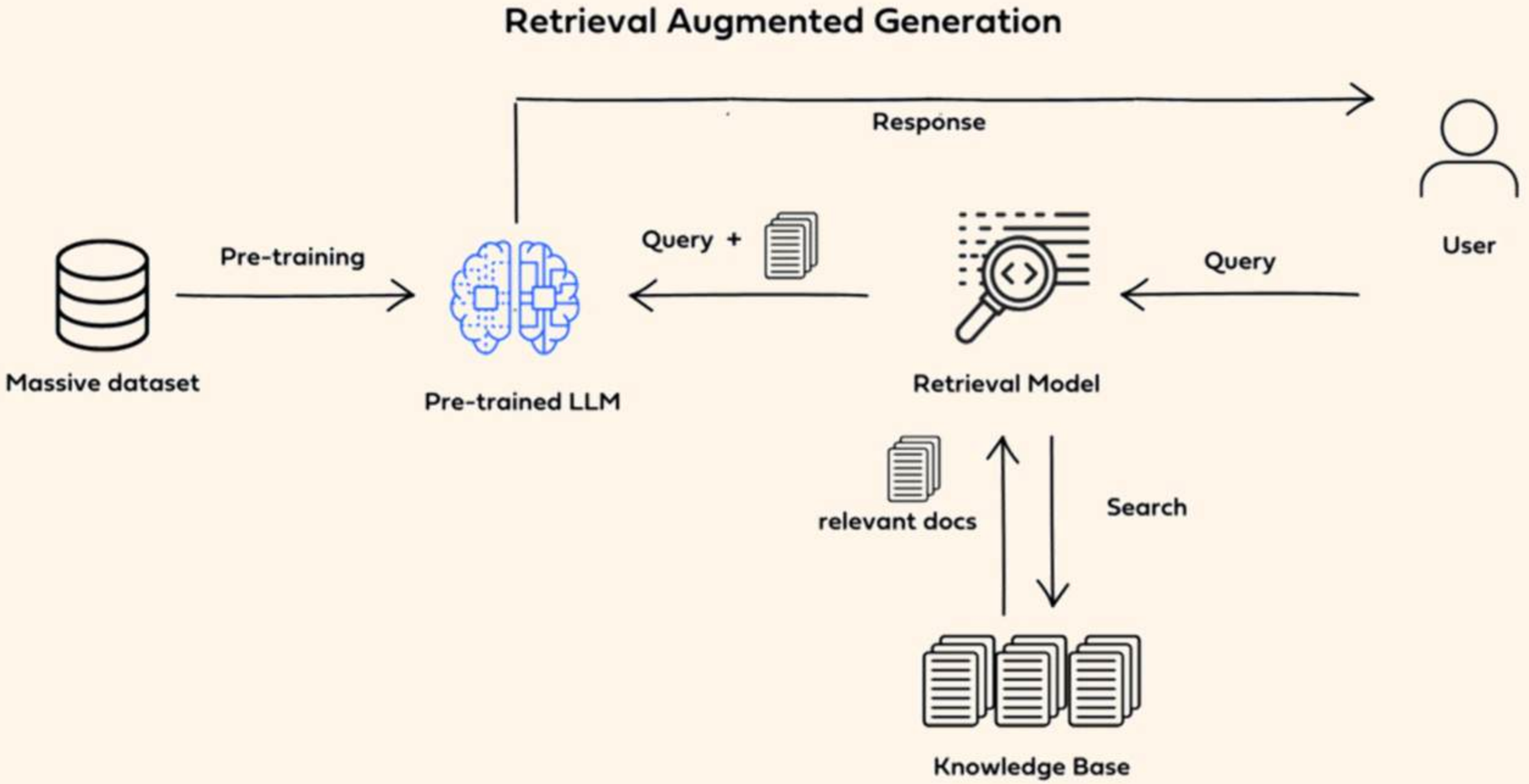
# Digital consulting

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# Digital consulting

Enter your question: can i use seaweed to reduce methane emission while not affecting milk yield?

The use of seaweed to reduce methane emission in dairy cows while not affecting milk yield is a topic of ongoing research. According to the provided context, some studies have shown that certain types of seaweed, such as Saccharina latissima, can increase milk yield and lactational performance in dairy cows without decreasing enteric methane emissions. However, other studies have found that the use of seaweed supplements, such as Asparagopsis taxiformis, can reduce methane emissions but may also have negative effects on animal health and performance. Therefore, the effectiveness of seaweed in reducing methane emissions while maintaining milk yield depends on the type and dosage of seaweed used, as well as other factors such as diet and management practices.

Here are the top 5 sources referenced:
1. Evaluation of 3 northwest European seaweed species on enteric methane production and lactational performance of Holstein-Friesian dairy cows (2023) - DOI: 10.3168/jds.2022-22749
2. Invited review: Advances in nutrition and feed additives to mitigate enteric methane emissions (2024) - DOI: 10.3168/jds.2023-24440
3. Effects of feeding algal meal high in docosahexaenoic acid on feed intake, milk production, and methane emissions in dairy cows (2013) - DOI: 10.3168/jds.2012-6168
4. Effect of the dietary supplementation with sunflower oil-enriched bromoform from Asparagopsis taxiformis on lambs' growth, health, and ruminal methane production (2024) - DOI: 10.1016/j.animal.2024.101249
5. Effects of early herbage cutting and vine leaves on methane emission, urine nitrogen losses, and the milk fatty acid profile of dairy cows (2022) - DOI: 10.3168/jds.2021-21458

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2. Invited review: Advances in nutrition and feed additives to mitigate enteric methane emissions (2024) - DOI: 10.3168/jds.2023-24440
3. Effects of feeding algal meal high in docosahexaenoic acid on feed intake, milk production, and methane emissions in dairy cows (2013) - DOI: 10.3168/jds.2012-6168
4. Effect of the dietary supplementation with sunflower oil-enriched bromoform from Asparagopsis taxiformis on lambs' growth, health, and ruminal methane production (2024) - DOI: 10.1016/j.animal.2024.101249
5. Effects of early herbage cutting and vine leaves on methane emission, urine nitrogen losses, and the milk fatty acid profile of dairy cows (2022) - DOI: 10.3168/jds.2021-21458

# Digital consulting

J. Dairy Sci. TBC:1–12
https://doi.org/10.3168/jds.2025-26775
JDS26775


## Agents are all you need: Pioneering the use of agentic artificial intelligence to embrace large language models into dairy science

E. Liu,[1]* H. Yang,[1] S. Sharma,[1] M. B. van Leerdam,[1] P. Niu,[1] M. J. VandeHaar,[2] and M. Hostens[1]*
[1]Department of Animal Science, Cornell University, Ithaca, NY 14850
[2]Department of Animal Science, Michigan State University, East Lansing, MI 48824

https://portal.bovi-analytics.com/

# Digital consulting

**Ask Bovi-Bot**

Can i use bromoform to reduce methane emissions

Based on the provided context, it appears that bromoform (CHBr3) has been shown to reduce methane emissions in ruminants. In the study "Effects of sunflower oil infusions of Asparagopsis taxiformis on in vitro ruminal methane production and biohydrogenation of polyunsaturated fatty acids," it was found that adding sunflower oil with increasing concentrations of CHBr3 to the diet of ruminants decreased methane production linearly, with reductions of 33%, 47%, and 87% at certain concentrations. This suggests that bromoform could be used to reduce methane emissions in livestock.

However, it is essential to note that the context does not provide information on the practical application of bromoform in reducing methane emissions on a large scale or its potential effects on animal health and productivity. Further research would be necessary to determine the feasibility and safety of using bromoform as a methane mitigation strategy in livestock production.

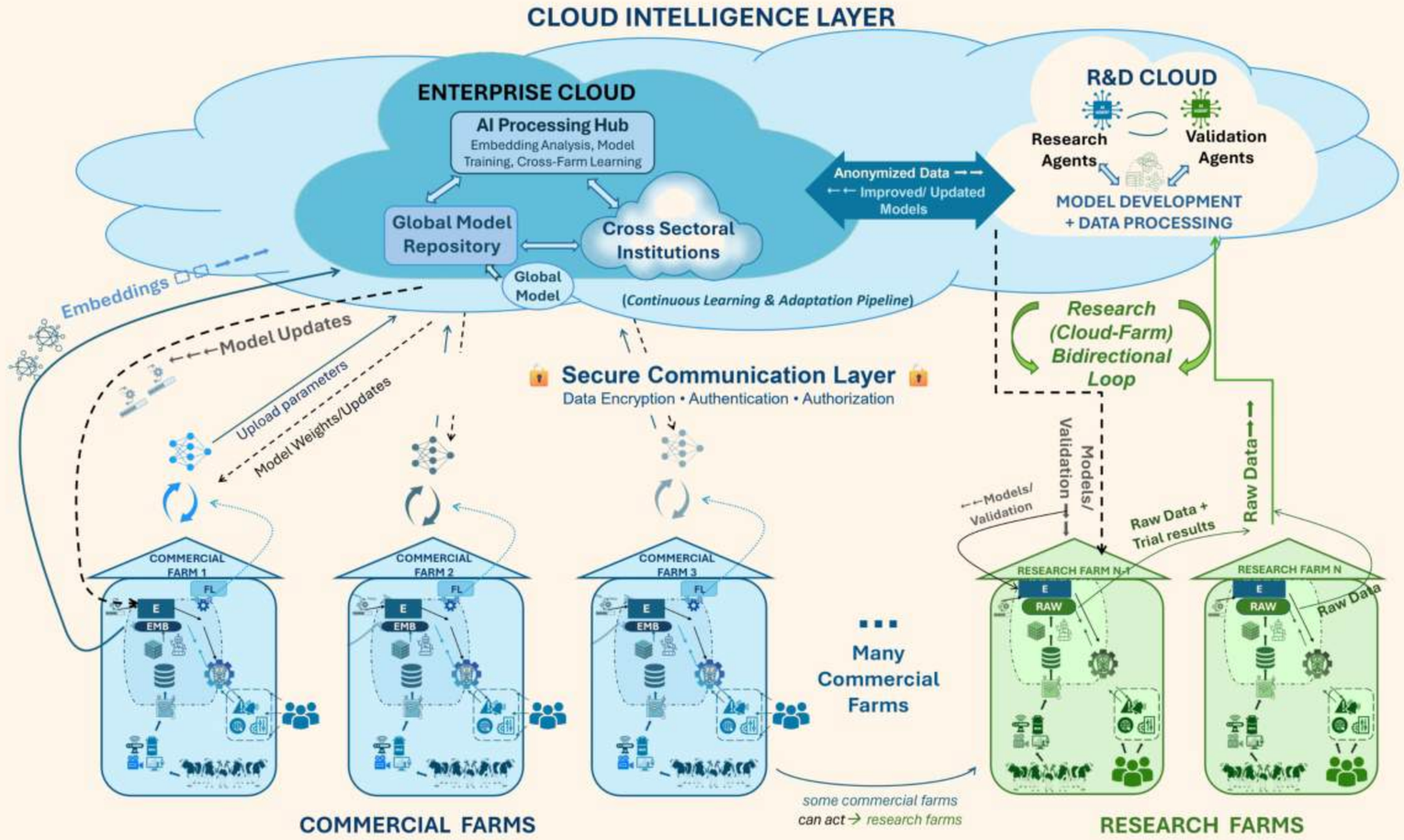
Here are the top 5 sources referenced:

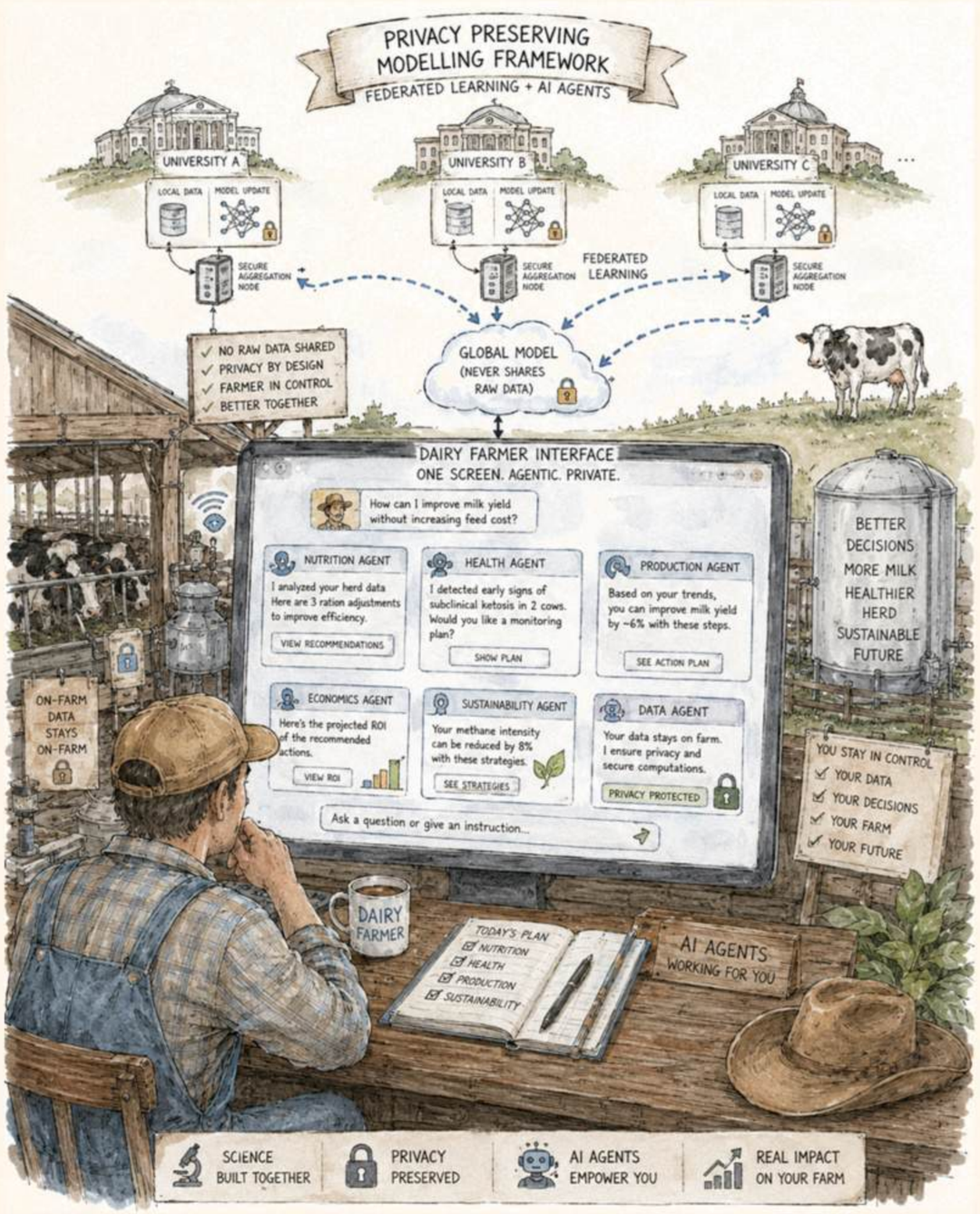
1. Effect of bromochloromethane on methane emission, rumen fermentation pattern, milk yield, and fatty acid profile in lactating dairy goats (2012) - DOI: 10.3168/jds.2011-4831
2. Review: Genetic and genomic selection as a methane mitigation strategy in dairy cattle (2020) - DOI: 10.1017/S1751731120001561
3. Short communication: Comparison of the GreenFeed system with the sulfur hexafluoride tracer technique for measuring enteric methane emissions from dairy cows (2016) - DOI: 10.3168/jds.2016-10897
4. Effects of sunflower oil infusions of Asparagopsis taxiformis on in vitro ruminal methane production and biohydrogenation of polyunsaturated fatty acids (2024) - DOI: 10.3168/jds.2023-23506
5. Performance and enteric methane emissions from housed beef cattle fed silage produced on pastures with different forage profiles (2023) - DOI: 10.1016/j.animal.2023.100726

what is the best treatment for endometritis

The best treatment for endometritis is not clearly defined in the provided context, as the studies mentioned have varying results and focus on different aspects of the disease. However, some studies suggest that certain treatments may not be effective, such as the use of prostaglandin F2α (PGF2α) or homeopathic remedies. On the other hand, a study on the application of a bacteriological on-farm test to reduce antimicrobial usage in dairy cows with purulent vaginal discharge found that a selective antibiotic treatment strategy based on the test results can reduce the number of required treatments while maintaining similar efficacy in terms of clinical cure and reproductive performance.

# Digital consulting




PRIVACY PRESERVING MODELLING FRAMEWORK
FEDERATED LEARNING + AI AGENTS
UNIVERSITY A
UNIVERSITY B
UNIVERSITY C
LOCAL DATA
MODEL UPDATE
SECURE AGGREGATION NODE
FEDERATED LEARNING
NO RAW DATA SHARED
PRIVACY BY DESIGN
FARMER IN CONTROL
BETTER TOGETHER
GLOBAL MODEL (NEVER SHARES RAW DATA)
DAIRY FARMER INTERFACE
ONE SCREEN. AGENTIC. PRIVATE.
How can I improve milk yield without increasing feed cost?
NUTRITION AGENT
I analyzed your herd data Here are 3 ration adjustments to improve efficiency.
VIEW RECOMMENDATIONS
HEALTH AGENT
I detected early signs of subclinical ketosis in 2 cows. Would you like a monitoring plan?
SHOW PLAN
PRODUCTION AGENT
Based on your trends, you can improve milk yield by ~6% with these steps.
SEE ACTION PLAN
ECONOMICS AGENT
Here's the projected ROI of the recommended actions.
VIEW ROI
SUSTAINABILITY AGENT
Your methane intensity can be reduced by 8% with these strategies.
SEE STRATEGIES
DATA AGENT
Your data stays on farm. I ensure privacy and secure computations.
PRIVACY PROTECTED
Ask a question or give an instruction...
BETTER DECISIONS MORE MILK HEALTHIER HERD SUSTAINABLE FUTURE
ON-FARM DATA STAYS ON-FARM
YOU STAY IN CONTROL
YOUR DATA
YOUR DECISIONS
YOUR FARM
YOUR FUTURE
DAIRY FARMER
TODAY'S PLAN
NUTRITION
HEALTH
PRODUCTION
SUSTAINABILITY
AI AGENTS WORKING FOR YOU
SCIENCE BUILT TOGETHER
PRIVACY PRESERVED
AI AGENTS EMPOWER YOU
REAL IMPACT ON YOUR FARM

# We are not there yet..

# We are not there yet..

- Who owns the model (multi-university & federally funded)?
- What is the $ value of this model (reward for farm data)?
- Should we open-source by default?
- How many of the published models made it to real world implementations?
- How do we transform this into something that actually works ...

BOVI-ANALYTICS

## Connect / more info / presentations

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- https://bovi-analytics.org

BOVI-ANALYTICS

CornellCALS
College of Agriculture and Life Sciences

# How artificial intelligence can transform an entire dairy industry, or NOT?

1982 - 2006 → AI → DATA → LIFECYCLE

*Challenges and opportunities*

Associate Prof. Dr. DVM Miel Hostens
Robert and Anne Everett Endowed Associate Professor of Digital Dairy Management and Data Analytics

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