

THE CHANGING MEANING OF FERTILITY IN DAIRY CATTLE

Editor

PROF. DR. MEHMET KÖSE

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Chairman of the Publishing House Group: Yusuf Ziya Aydoğan (yza@egitimyayinevi.com)

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Interior Designer: Kübra Konca Nam

Cover Designer: Kübra Konca Nam

Republic of Türkiye Ministry of Tourizm and Culture

Publisher Certificate No: 76780

E-ISBN: 978-625-385-767-7

1. Edition, january 2026

Library Information Card

THE CHANGING MEANING OF FERTILITY IN DAIRY CATTLE

Editor: Prof. Dr. Mehmet Köse

V+78, 135x215 mm

Includes references, no index.

E-ISBN: 978-625-385-767-7

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Publisher Turkey Office: İstanbul: Eğitim Yayinevi Tic. Ltd. Şti., Atakent mah. Yasemen sok. No: 4/B, Ümraniye, İstanbul, Türkiye

Konya: Eğitim Yayinevi Tic. Ltd. Şti., Fevzi Çakmak Mah. 10721 Sok. B Blok, No: 16/B, Safakent, Karatay, Konya, Türkiye
+90 332 351 92 85, +90 533 151 50 42
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Publisher USA Office: New York: Egitim Publishing Group, Inc.
P.O. Box 768/Armonk, New York, 10504-0768, United States of America
americaoffice@egitimyayinevi.com

Logistics and Shipping Center: Kitapmatik Lojistik ve Sevkiyat Merkezi, Fevzi Çakmak Mah. 10721 Sok. B Blok, No: 16/B, Safakent, Karatay, Konya, Türkiye
sevkiyat@egitimyayinevi.com
E-Commerce: +90 553 950 50 37

Bookstore Branch: Eğitim Kitabevi, Şükran mah. Rampalı 121, Meram, Konya, Türkiye
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List of Abbreviations

&	And
ADI	Acceptable Daily Intake
AI	Artificial insemination
AI	Artificial intelligence
BVDV	Bovine viral diarrhea virus
CAC	Codex Alimentarius Commission
CIDR	Controlled internal drug release device
EC	European Commission
EP	European Parliament
ET	Embryo Transfer
EU	European Union
FAO	Food and Agriculture Organization
GnRH	Gonadotropin Releasing Hormone
IGF 1	Insulin Like Growth Factor 1
IOVCR	Illinois Office of the Vice Chancellor for Research
IVF	In Vitro Fertilization
JECFA	Joint FAO/WHO Expert Committee on Food Additives
ML	Machine learning
MRL	Maximum Residue Limits
NEB	Negative Energy Balance
PGF2 α	Prostaglandin F 2 alfa
SCC	Somatic Cell Count
TAI	Timed Artificial Insemination
THI	Temperature-Humidity Index
WHO	World Health Organization
WOAH	World Organisation for Animal Health

Preface

For a long time, fertility in dairy herds was summarized through a small set of indicators in reproductive performance tables. It is now evident that fertility is shaped by postpartum biology and by the broader system in which cows are managed. Energy balance, uterine health, disease pressure in the postpartum period, environmental stress, data infrastructure, and farm economics interact and determine reproductive outcomes.

This book was developed from the need to address these drivers as connected components of a single management system. The chapters bring together transition period physiology, metabolic and uterine disorders, environmental and managerial factors, estrus detection and sensor based monitoring, hormone based reproductive protocols, and economic evaluation. The text also positions fertility improvement within a sustainability perspective that includes welfare considerations and societal expectations.

While preparing the chapters, priority was given to conceptual consistency, a comprehensive style, and explanations grounded in practical field examples. The goal is not only to increase pregnancy rate. The goal is to support healthier and longer lived herds, a more stable farm economy, and decision routines that remain defensible in modern production systems. If the book encourages the reader to reconsider even a small number of critical choices in their own herd or advisory work, it will have fulfilled its purpose.

Editor

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INTRODUCTION

Mehmet Köse¹

A central determinant of profitability in dairy enterprises is the ability to obtain a healthy calf from each cow at regular intervals. Calving interval, days open, and pregnancy rate shape milk yield distribution across the year and they influence replacement pressure and cash flow stability (Arbel et al., 2001; De Vries, 2006; Inchaisri et al., 2010). When fertility deteriorates, the loss is rarely limited to a lower conception rate. The herd also faces more inseminations, more involuntary culling, and higher replacement needs, which collectively erode long term efficiency (De Vries, 2006; Inchaisri et al., 2010).

In high producing herds, fertility is best understood as a system property rather than a single event. Postpartum biology links negative energy balance, endocrine function, ovarian activity, and embryo survival in a tightly connected chain (Lucy, 2001; Butler, 2003; Walsh et al., 2011). The rapid rise in energy demand after calving can exceed the increase in feed intake. This imbalance delays cyclicity and is associated with weaker luteal function and higher early pregnancy loss risk (Butler, 2003; Walsh et al., 2011). Uterine health is another limiting axis. Postpartum metritis and endometritis can compromise reproductive outcomes by prolonging inflammation and delaying uterine recovery (LeBlanc, 2008).

Environmental and managerial conditions further shape fertility outcomes by altering both physiology and estrus expression. Heat stress is consistently associated with reduced oocyte competence, impaired embryo development, and lower conception rate (Al Katanani et al., 2002; De Rensis et

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al., 2017). Evidence also indicates that heat exposure affects fertility across a broader window that includes the weeks before insemination and the early post insemination period, which helps explain seasonal declines in pregnancy rate (Morton et al., 2007). Housing design, stocking density, lying time, and lameness influence welfare and they can suppress mounting behavior and visible estrus. This creates practical limits for visual observation, especially as herd size and workload increase (Polsky & von Keyserlingk, 2017; Tucker et al., 2021).

Against this background, digital monitoring has shifted fertility management toward continuous measurement and earlier intervention. Activity sensors, pedometers, ear tag systems, and integrated milking line data can support estrus detection and help identify transition period risks that indirectly reduce fertility (Neves et al., 2012; Mottram, 2016; Cerri et al., 2021). Recent work shows that machine learning models can use farm records and sensor streams to estimate pregnancy probability and to flag disease risk earlier than clinical observation alone (Ryan et al., 2020; Barden et al., 2024; Džermeikaitė et al., 2025). At the same time, these tools require careful attention to data quality, calibration, and generalizability across herds, otherwise alerts can become noise rather than decision support (Grzesiak et al., 2025).

Hormone based timed artificial insemination programs remain a major strategy for herds where estrus detection is inconsistent. Synchronization approaches can reduce time loss between breeding opportunities and can improve service rate under conditions of suppressed estrus expression (Wiltbank & Pursley, 2014; Wiltbank et al., 2015). Economic analyses emphasize that the value of these programs depends on herd context, labor constraints, and the baseline efficiency of estrus detection (Giordano et al., 2011; Galvão et al., 2013). Protocol design also matters, because small modifications that improve luteolysis or alignment of ovulation can change net returns in realistic farm scenarios (Borchardt et al., 2021; Fricke & Wiltbank, 2022).

This volume synthesizes biological, environmental, technological, and economic layers within a unified management narrative. Chapter 2 examines heat detection and digital monitoring processes, emphasizing how sensor data analysis can support field decisions. Chapter 3 is dedicated to designing breeding programs and hormonal protocols within the context of risk-based herd segmentation. Chapter 4 evaluates the economic rationale for hormonal protocols as structured decision tools rather than routine habits. Chapter 5 explores herd structure, renewal dynamics, and transition health as interactive drivers of long-term resilience.

The primary audience of the book consists of veterinarians, animal scientists and livestock consultants working in dairy enterprises, together with graduate students and researchers in this field. Throughout the text, attention is given both to the explanation of key concepts and to practical problems encountered in the field. The intention is not only to provide theoretical information but also to offer an evidence based decision framework that helps the reader rethink fertility management in their own herd or advisory context.

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Chapter 2.

ESTRUS DETECTION AND DIGITAL MONITORING IN FERTILITY MANAGEMENT

Gaye Bulut¹

Fertility performance in dairy herds is one of the most sensitive determinants of profitability. Pregnancy rate, calving interval and days open have direct effects on production cost and lifetime milk yield per cow (Arbel et al., 2001; De Vries, 2006). Fertility management is therefore not only a biological issue. It is also a central component of herd level decisions on replacement, labor use and investment planning.

This chapter discusses how environmental and managerial factors, estrus detection strategies and digital fertility monitoring tools shape fertility dynamics. The aim is to integrate classical behavioral observation with sensor technologies and data driven decision support in a coherent management framework.

2.1 Estrus Behavior and Classical Detection Methods

Accurate identification of estrus at the right time is a basic requirement for successful fertility management. Negative energy balance, heat stress and health problems can weaken the expression of estrus. Traditional visual observation is still widely used, but in large herds it is time consuming and prone to human error.

Technological progress has brought important advances in estrus detection. Activity meters, pedometers, pressure sensitive devices, thermal cameras and artificial intelligence supported image analysis systems can record estrus related changes with high precision (Senger, 1994; Xu et al., 1998).

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These systems reduce labor demand and help avoid timing errors, which contributes to higher pregnancy rates.

High milk production and energy deficit may suppress estrus behavior. Changes in group dynamics, locomotion and social interaction make visual detection more difficult. As herd size and workload increase, the added value of sensor based monitoring becomes more evident. These tools improve the timing of insemination and reduce dependence on individual staff skills (Lopez et al., 2004).

In modern dairy cows, estrus detection has become even more challenging. Estrus periods are shorter, behavioral signs are less intense and expression can be subtle. High milk yield, energy deficit, heat stress and metabolic disease reduce both the frequency and intensity of estrus signs. As a result, the sensitivity of classical detection methods decreases (Senger, 1994; Roelofs et al., 2005; Reith and Hoy, 2018).

Visual observation is the oldest and most widely used approach. It is based on regular evaluation of behaviors that increase before insemination. These include higher activity, mounting, standing to be mounted, sniffing, licking and restlessness (Saint Dizier & Chastant Maillard, 2012; Palomares, 2021).

Effective visual observation programs usually recommend at least 2 or 3 periods of 15 to 20 minutes per day. In practice, high workload, limited staff and housing design often prevent consistent implementation. In high producing cows, estrus periods are shorter and peak activity often occurs at night. This increases the proportion of missed estrus episodes in programs that rely only on visual observation (Roelofs et al., 2005; Saint Dizier and Chastant Maillard, 2012).

Pedometers and activity meters were among the first technological aids added to visual observation. These systems measure step count or activity level during specified time intervals and identify the increase in movement that accompanies estrus. In the study by Xu and colleagues, pressure sensors and

activity systems were compared with visual observation. Both pedometers and pressure sensors reached higher detection rates than visual observation alone, although sensor loss and false alarms still limited performance (Xu et al., 1998).

Several studies have shown that activity data are useful for both estrus detection and estimation of time of ovulation. When appropriate thresholds are set, detection rates can increase substantially compared with visual observation alone (Firk et al., 2002; Roelofs et al., 2005).

Tail paint or tail chalk provides a simple and low cost complement to visual observation. Paint is applied on the tail head. During estrus, mounting behavior causes rubbing and removal or smearing of the paint. This allows rapid identification of cows with a high probability of estrus in the pen. When combined with activity sensors, tail paint can increase both sensitivity and specificity of estrus detection. It also helps interpret sensor alerts and refine insemination timing (Fricke, 2002; Cerri et al., 2021).

Tail paint is particularly useful at the end of timed artificial insemination protocols. In this context it serves as a practical field indicator of estrus activity and possible ovulation. When interpreted together with activity data, tail paint can contribute to better insemination timing at the end of hormone programs. This suggests that tail paint can be used not only for estrus detection but also as a rapid field tool to assess protocol performance (Cerri et al., 2021).

Group dynamics and social behavior are often overlooked, although they provide important practical clues. During estrus, cows become more active, form small subgroups, increase contact with herd mates and show more mounting attempts. These behaviors are particularly evident in free stall systems and pasture based herds (Roelofs et al., 2005; Saint Dizier and Chistant Maillard, 2012). High stocking density, slippery floors, uncomfortable resting areas and severe heat stress may suppress mounting and activity. In such conditions

it becomes difficult to make use of group behavior. Review papers underline that under modern housing conditions estrus behavior is shorter and less obvious. They recommend that behavioral assessment should be supported by other methods (Marques et al., 2020; Reith and Hoy, 2018).

In summary, visual observation, pedometers, tail paint and group behavior assessment are complementary components of classical estrus detection. Visual observation is indispensable for qualitative evaluation of behavior. Activity sensors provide quantitative support. Tail paint is a practical screening tool, especially in large herds. Careful monitoring of group dynamics helps interpret all these data in a behavioral context (Senger, 1994; Fricke, 2002; Lopez et al., 2004).

Even so, in high producing herds these four elements are no longer sufficient on their own. Integration with sensor based systems and artificial intelligence supported analytics is needed. Such integration maintains the strengths of classical methods, but reduces human error and time pressure. It shifts fertility management toward a more predictable and data oriented structure (Saint Dizier and Chastant Maillard, 2012; Palomares, 2021).

2.2 Environmental Stress, Temperature Humidity Index and Housing Management

Environmental stress, especially heat stress expressed through the temperature humidity index (THI), is one of the most important external factors that reduce fertility. Heat stress affects follicular development, oocyte quality, embryo survival and the uterine environment in a negative way (Al Katanani et al., 2002; De Rensis et al., 2017). Reduced pregnancy rates in summer are a typical field manifestation of these effects.

When THI increases, oocyte competence, early embryonic development and conception rate decline. This also raises the risk of embryonic loss during the peri implantation period. Appropriate cooling strategies and adjustment of breeding schedules help maintain pregnancy rates during hot seasons

(Al Katanani et al., 2002; Morton et al., 2007; De Rensis et al., 2017).

Producers use several tools to reduce heat load. Shade structures, combinations of fans and water sprays, evaporative cooling systems and appropriate housing design are among the most common solutions. Climate change and more frequent extreme heat events will increase the importance of environmental management in future fertility programs. High stocking density and poor housing conditions also increase social stress and metabolic load. Both factors can suppress estrus behavior and reduce fertility (Ptaszyńska, 2023).

THI has become a central tool to quantify the effect of environmental stress on fertility. Increased THI is associated with lower feed intake and milk yield, as well as reduced oocyte competence, impaired early embryo development and decreased conception rate (Al Katanani et al., 2002; Dash et al., 2016; De Rensis et al., 2017). In high producing cows, heat stress can start at THI values around 68. At values of 72 and above, significant reductions in pregnancy rate have been reported in different climates (Morton et al., 2007; Kadzere et al., 2002). For this reason, herd level fertility analysis should not focus only on service index or pregnancy rate. Daily or weekly THI profiles for the same periods should also be evaluated.

The impact of heat load on fertility is not limited to the insemination day. High THI on the day of insemination is critical, but the period 3 to 5 weeks before insemination and the first week after insemination are also important. These windows have been identified as high risk for embryo loss and reduced conception (Morton et al., 2007; Dash et al., 2016). In embryo transfer (ET) programs, pregnancy rates also decline on days with THI above 75. Even if transferred embryos are relatively tolerant to heat, pregnancy is compromised when body temperature of the recipient cow rises (Nishisou et al., 2023). These findings show that heat stress imposes a

cumulative burden on preovulatory follicle development and the peri implantation period. Fertility programs should therefore be planned with these time windows in mind.

Housing design and cooling strategies are key areas of intervention to protect fertility under heat stress. Shade, natural and mechanical ventilation, combinations of fans and water sprays, and localized evaporative cooling in holding pens and feed alleys can reduce both rectal temperature and respiration rate. Several studies report associated improvements in pregnancy rate (Kadzere et al., 2002; Becker et al., 2020). Effective cooling in late lactation and the dry period may improve fertility in the next lactation together with milk yield. Reducing the number of days with THI above 68 is particularly beneficial for conception at first service (Ferreira et al., 2016; Allen et al., 2015). For sensitive periods, housing design should consider air flow, shade, water availability and space per cow as parts of a single system.

Stocking density links heat load and behavioral stress. In free stall barns, higher numbers of cows per stall shorten lying time and increase standing time and exposure to heat. Social stress and competition also intensify (Krawczel and Lee, 2019; Tucker et al., 2021). Cows under heat stress tend to stand longer to increase heat loss. Under high stocking density this behavior can worsen hoof health, rumen function and estrus behavior (Allen et al., 2015; Polsky and von Keyserlingk, 2017). Proper stocking density and effective cooling must be planned together to protect both comfort and fertility when THI is high (Ptaszyńska, 2023; De Rensis et al., 2017).

Recent approaches integrate THI data and barn climate sensors with herd management software. The goal is to predict fertility losses caused by heat stress. When barn temperature and humidity sensors are combined with cow level data on activity, rumination and body temperature, it becomes possible to identify high risk animals during hot days in terms of feed intake and estrus behavior (Becker et al., 2020; Balhara et

al., 2021). Decision support tools built on these data allow rescheduling of inseminations, adjustment of synchronization protocols and more targeted use of cooling infrastructure. In this way, THI, heat stress, cooling strategies and stocking density are brought together within a single management framework. Fertility losses can be reduced while still aligning with environmental sustainability goals.

2.3 Sensor Based Monitoring Systems

In dairy herds, sensor based monitoring has transformed fertility from a parameter checked at discrete time points into a dynamic process under continuous observation. Neck collars, ear tags, leg mounted pedometers, rumen boluses and sensors integrated into milking systems collect multiple behavioral and physiological signals in real time. These systems track changes in activity, rumination, body temperature, feed intake, milk yield and locomotion. This makes it possible to detect early biological signals related to fertility (Neves et al., 2012; Mottram, 2016).

Automated activity monitoring can reach higher sensitivity and better timing than visual observation. In the study by Neves and colleagues, an automated activity based program was compared with a timed artificial insemination program that relied on synchronization. Herds using activity monitoring achieved estrus detection and pregnancy outcomes that were at least similar and in many cases better. At the same time, dependence on hormone protocols decreased, which reduced drug costs and avoided unnecessary hormone treatments (Neves et al., 2012).

Adding rumination and behavior data to activity signals allows a more refined description of estrus. In studies that combined activity and rumination, estrus periods were characterized not only by an increase in activity but also by a short and temporary decrease in rumination time. This pattern has been proposed as a relatively specific signature for estrus (Pereira et al., 2020). Such multi sensor systems are especially

valuable in free moving and pasture based herds. They can detect silent estrus cases that are often missed by systems based solely on activity (Mottram, 2016; Pereira et al., 2020).

Sensor based systems are also important for early detection of transition period risks and subclinical disease. Small but consistent changes in rumination time, milk yield, milk composition and body temperature can reveal metritis or disorders of energy balance before clinical signs appear. Machine learning models developed for metritis have used rumination, milk yield and milk components as predictors. These models reached high sensitivity and specificity for early diagnosis (Džermeikaitė et al., 2025). Integrating such models into clinical decision support systems helps manage health problems that indirectly impair fertility.

In recent years, ear tag accelerometers have enabled a more detailed analysis of behavior related to fertility. Studies using 2 years of behavioral data have shown that patterns of rumination and lying time derived from ear tag sensors predict pregnancy status with high accuracy (Cavallini et al., 2025). These results indicate that sensor data can be used not only for estrus detection but also for pregnancy confirmation and early detection of possible pregnancy loss. In practical settings, these systems can generate prioritized lists of high risk animals. This supports timely veterinary intervention and reduces production losses (Neves et al., 2012; Cavallini et al., 2025).

The effectiveness of sensor based systems depends heavily on data quality and interpretation. Poorly attached sensors, weak wireless connections, software problems and integration issues with herd management programs can produce false positive and false negative alerts. Lameness, severe heat stress or sudden changes in housing conditions may alter activity and behavior and generate estrus like patterns. For this reason, sensor data should not be interpreted in isolation. They need to be evaluated together with clinical examination and sound record keeping (Mottram, 2016; Denis Robichaud et al., 2018).

For effective fertility management, several conditions are essential. Sensor systems must be calibrated correctly. Alert thresholds should be adapted to each herd. Staff need training to interpret data and distinguish meaningful patterns from noise (Smith et al., 2014). Under these conditions, sensors can become powerful tools rather than sources of confusion.

2.4 Artificial Intelligence and Data Analytics for Early Warning Systems

Artificial intelligence and data analytics are pushing fertility management toward a more fully data driven structure. Automated activity monitoring, milk yield and milk composition sensors, rumen boluses, environmental sensors and herd management software generate large volumes of data. Machine learning and other artificial intelligence methods can analyze these multi dimensional data sets and produce dynamic risk profiles for each cow. This shifts fertility management from a reactive model based on realized outcomes to a proactive model based on predicted probabilities (Ryan et al., 2020; Grzesiak et al., 2025).

Artificial intelligence models are particularly prominent in estrus detection and prediction of pregnancy probability. In studies that used activity data together with animal specific and environmental records, models were able to estimate the probability of pregnancy following insemination. These models outperformed strategies that relied only on activity alerts to time insemination (Campos Marques et al., 2024). Other work has compared logistic regression with advanced machine learning algorithms to predict pregnancy risk using herd data. Ensemble models have achieved high accuracy in predicting changes in pregnancy probability (Barden et al., 2024). These findings suggest that artificial intelligence based decision support can optimize both timing and cow selection for insemination.

Machine learning has also been applied to early prediction of transition diseases that impair fertility. For metritis, models

have used routinely recorded variables such as milk yield, milk components, rumination time and body temperature. These models can identify high risk cows before clinical signs appear, with high sensitivity and specificity (Džermeikaitė et al., 2025). Some models that use neural networks and ensemble methods have reported sensitivities above 90 while maintaining good specificity. The fertility relevance of such systems lies in timely treatment of metritis and similar uterine infections. Early intervention shortens the period to return to service, increases pregnancy rate and reduces unnecessary treatment costs.

Similar patterns are reported in models that predict fertility and milk yield together. Studies that used artificial neural networks and gradient boosting have achieved higher predictive accuracy and better generalization compared with traditional statistical methods (Kilani et al., 2025). Review papers emphasize increasing use of logistic regression, decision trees, random forests, support vector machines and deep learning for prediction of reproductive performance and other health and production indicators (Grzesiak et al., 2025). This growing evidence base shows that artificial intelligence based early warning systems are becoming powerful tools not only at cow level but also for strategic planning at herd level.

The practical value of early warning systems depends on their integration into real farm decision processes. Cloud based platforms can process large data sets from farms in real time. They then present risk scores, optimal time windows for insemination and alerts for animals requiring intervention in simple user interfaces (Balhara et al., 2021; Ryan et al., 2020). These systems can highlight cows at high risk of metritis, candidates with low expected pregnancy probability or groups with elevated risk of fertility decline due to heat stress. Veterinarians and farmers can then prioritize their time and interventions. This leads to more targeted clinical work and avoids unnecessary drug use and labor.

Artificial intelligence and data analytics also have limitations. Training data sets usually reflect the conditions of

specific farms or regions. When the same models are applied to herds in other environments or management systems, performance can decline due to lack of generalizability. Data quality issues, sensor failures and inconsistencies in record keeping can further reduce model accuracy. Some complex models have low transparency, which makes interpretation of results difficult for users in the field (Grzesiak et al., 2025). Future work needs to improve generalizability, develop explainable artificial intelligence approaches and carry out prospective trials in different ecological regions.

Taken together, artificial intelligence and data analytics transform sensor data into biologically and managerially meaningful signals. They increase early warning capacity in fertility management. Heat stress, transition diseases and management failures that impair fertility can be detected earlier and addressed with more targeted interventions. This contributes to higher pregnancy rates, shorter days open, reduced antibiotic use and lower greenhouse gas emissions. These outcomes support both economic and environmental sustainability goals in dairy production (Garnsworthy, 2019; Campos Marques et al., 2024).

2.5 Economic Impact and Field Applications

Fertility performance is one of the most sensitive drivers of profit in dairy herds. Small changes in pregnancy rate, days open, parity distribution and involuntary culling can create large cumulative effects on milk output, number of calves and cull income over time. Dynamic simulation models show that higher pregnancy rate and shorter days open have clear positive effects on net profit (De Vries, 2006; Barden et al., 2024). The same improvements reduce unnecessary rearing of surplus heifers, avoid premature culling and limit costly replacement decisions (Overton and Dhuyvetter, 2020). Better fertility and more lactations per cow increase lifetime milk yield and spread fixed costs over more kilograms of milk (Garnsworthy, 2019).

Digital monitoring and artificial intelligence supported systems strengthen this economic impact through 2 main channels. First, they improve estrus detection and insemination timing, which increases the probability of pregnancy. Second, they enable earlier detection of transition diseases such as metritis and energy balance disorders that indirectly reduce fertility. In herds using automated activity monitoring, several studies have reported similar or better reproductive performance compared with synchronization based fixed time programs. Labor demand often decreases at the same time (Neves et al., 2012; Kamphuis et al., 2010). Machine learning models that combine sensor data and herd records can predict pregnancy risk, number of services and length of the service period with high accuracy. This allows more economically rational insemination decisions (Caraviello et al., 2006; Campos Marques et al., 2024; Barden et al., 2024).

Economic evaluations of automated estrus detection systems generally indicate positive net returns in many scenarios. Studies of activity meters report positive annual net income per cow and in some scenarios more than 10 euros of additional annual profit per cow (Pfeiffer et al., 2020; Adenuga et al., 2020). The main sources of these gains are higher milk yield, shorter days open, more calves and savings in hormone protocols and labor (Giordano, 2015; Adenuga et al., 2020). Recent simulation analyses of sensor supported health and fertility management show that rumen bolus systems also have potential to generate additional net profit of several tens of euros per cow per year in high producing herds (Pfrombeck et al., 2025). These results are, however, very sensitive to assumptions about milk price, investment cost, sensor life and consistency of management.

Comparative studies of reproductive programs indicate that sensor based systems can be used together with hormone protocols or as partial alternatives. Timed artificial insemination programs can bring economic benefits in herds where estrus detection is weak, because they increase pregnancy rate

and stabilize reproductive performance (Borchardt et al., 2021). In herds that achieve high estrus detection efficiency, combinations of automated activity monitoring and targeted hormone use can reduce protocol costs while maintaining similar pregnancy rates with less drug use and less labor (Neves et al., 2012; Wicaksono et al., 2024). These findings show that hormone programs and sensor based systems are not opposing choices. They are complementary tools that can be combined in different ways depending on herd structure.

Field experience indicates that investment decisions should not depend only on theoretical profitability calculations. Organization of the farm and quality of human resources are equally important. In large and multi shift herds, especially where staff turnover is high, sensor systems can provide continuity and reduce the negative impact of personnel changes on fertility management. In robotic milking herds, where data on milk yield, milk composition and milking frequency are already abundant, adding sensor data further improves the performance of pregnancy prediction and risk scoring models (Cavallini et al., 2025; Ryan et al., 2020).

In small and medium sized herds, attractiveness of investment is more limited by initial costs, capacity to use the technology and access to technical support. For these herds, lower cost pedometers or neck collars combined with simple decision support tools may be more realistic first steps (Thomas et al., 2019; Adenuga et al., 2020). A gradual strategy that starts with basic sensors and good records, then moves toward more advanced decision support, is often more feasible.

Overall, sensor based fertility monitoring and artificial intelligence supported decision systems can be profitable investments when they are properly designed and implemented. They increase direct revenues and reduce disease related losses and labor demand. Their economic success, however, depends on farm specific feasibility analysis, robust record systems and adequate training of users. Without these conditions, sensors

may remain alarm generating devices without translating into better economic outcomes.

In conclusion, sensor based monitoring systems and artificial intelligence applications are transforming fertility management in dairy herds. Management is shifting from a reactive model that responds to events after they occur to a proactive model that anticipates risks. Continuous monitoring of activity, rumination, milk yield, milk composition, body temperature and environmental parameters provides a strong data base for estrus detection and early diagnosis of transition diseases (Kamphuis et al., 2010; Ryan et al., 2020). This shift increases pregnancy rate and shortens days open. At the same time it reduces unnecessary drug use and premature culling and supports animal welfare and environmental sustainability (Garnsworthy, 2019).

Management guidelines need a stepwise and flexible structure. It is neither realistic nor necessary for all herds to use the same technologies at the same intensity. The primary goal is to build data based decision processes that fit herd structure, climate, feeding strategy and labor conditions. For this reason, the first step is to organize record keeping. Sensor systems should be integrated gradually after a basic data infrastructure is in place. Without reliable records, technological investments produce data that are difficult to interpret and limit economic potential (Ruegg, 2017; Smith et al., 2014).

For small and medium sized herds, the initial focus should be on simple but reliable estrus monitoring. Neck collars or leg mounted pedometers are relatively affordable options. When combined with regular body condition scoring, uterine examination and disciplined record keeping, these systems can offer clear advantages compared with visual observation alone (Neves et al., 2012; Kamphuis et al., 2010). In such herds, hormone protocols can be planned in a more targeted way based on sensor alerts. This reduces unnecessary treatments and limits costs related to metritis and other transition

problems (Džermeikaitė et al., 2025; De Rensis et al., 2017). A reasonable strategy for these herds is to start with records and basic sensors, then introduce reproductive programs for defined risk groups.

Management strategies differ in herds with robotic milking or high data density. These herds already generate continuous data on milk yield, milk composition, milking frequency and activity. The first priority is to integrate these data into a single platform and link them to models that predict pregnancy probability, metritis risk and energy balance status (Ryan et al., 2020; Campos Marques et al., 2024). Adding behavior and health data from ear tags and rumen boluses can further improve prediction of pregnancy and disease (Cavallini et al., 2025; Pfrombeck et al., 2025). In such herds, management guidelines should be based on daily automated reports that list high risk cows, suggest insemination candidates for the next day and identify animals that should receive veterinary examination. This converts dense data streams into practical and actionable decisions.

In hot climates, fertility management must emphasize strategies that counteract heat stress. Combining THI data with activity and rumination records helps decide when hormone programs should support estrus detection (De Rensis et al., 2017). To minimize losses in milk yield and pregnancy, cooling systems, shade and feeding strategies need to be evaluated together with sensor data. Early morning and late evening inseminations, timed artificial insemination protocols and special follow up programs for high risk cows can be aligned with sensor alerts to improve fertility under heat stress (Garnsworthy, 2019).

Across all scenarios, staff training and data literacy are critical. Veterinarians, animal scientists and farmers need to understand the meaning of sensor signals, how to recognize false positives and false negatives and how to interpret artificial intelligence based risk scores (Wicaksono et al., 2024; Grzesiak

et al., 2025). National policies on data security, ethics and data sharing should encourage multi farm studies and development of large data bases. Such frameworks will make it easier to combine data from different ecological regions under common standards and to develop more reliable and generalizable models (Ryan et al., 2020).

The management framework described in this chapter points to a multi layer fertility strategy. Sensor systems and artificial intelligence are integrated with hormone protocols and classical clinical examination. The objective is not to identify a single ideal protocol, but to build combinations of tools that are economically, technically and organizationally feasible for each herd. Programs designed in this way can increase pregnancy rates, reduce use of antibiotics and hormones, limit greenhouse gas emissions and extend the productive life of cows (De Vries, 2006; Garnsworthy, 2019). This provides a solid basis to respond to current clinical and economic challenges and to adapt dairy production to future pressures from climate change and evolving societal expectations.

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Chapter 3.

DESIGN OF REPRODUCTIVE PROGRAMS AND HORMONAL PROTOCOLS IN DAIRY COW HERDS

Şükrü Dursun¹

Fertility control programs in dairy herds are integrated management frameworks that aim to monitor and improve reproductive performance. These programs are not limited to the treatment of individual animals. They also require systematic recording at herd level, structured risk assessment, and timely diagnosis and intervention.

Economic returns depend on shortening the interval from calving to conception, improving first service conception rate, and reducing pregnancy losses (De Vries, 2006; Ptaszyńska, 2023). A successful fertility control program therefore depends on the coordination of technical, economic, and organizational components. Management errors can limit the impact of even the most sophisticated hormonal protocols. Program design is not only a list of treatments. It also represents a reorganization of decision making in the herd.

3.1 Program Design

Reproductive program design in dairy herds focuses on managing pregnancy rate at herd level rather than treating individual cows in isolation. Several indicators form the core of this design. These include service interval, days open, 21 day pregnancy rate, pregnancy per insemination, embryonic

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loss, and culling due to infertility (Esslemont and Kossaibati, 2002; De Vries, 2006; Ptaszyńska, 2023).

Regular monitoring of these indicators reveals weak points in the system. For example, if pregnancy per insemination is acceptable but days open are prolonged, the problem is often delayed insemination or poor pregnancy diagnosis. When both days open and pregnancy rate are unsatisfactory, deficiencies in estrus detection or a high burden of uterine disease become more likely explanations (Walsh et al., 2011; Ribeiro et al., 2013).

3.1.1 Performance Targets and Threshold Values

The first step in program design is to define explicit targets. Common thresholds include keeping average days open below approximately 130, achieving first service pregnancy rates of at least 50 in heifers and 35 or more in cows, and maintaining a 21 day pregnancy rate between 25 and 30 (De Vries, 2006; Inchaisri et al., 2010; Giordano, 2019).

These thresholds should not be copied directly from other herds. Feeding level, climate, herd size, labor organization, and genetic merit must be considered when setting realistic goals. In hot climates for example, it can be practical to accept lower pregnancy rates during summer and expect higher performance in the cooler season (De Rensis et al., 2017).

3.1.2 Data Quality, Recording Systems, and Decision Support

Economic modeling shows that higher pregnancy rate reduces days open, lowers replacement needs, and increases milk income (De Vries, 2006; Inchaisri et al., 2010). These models only have value when based on reliable data. Dates of calving, each insemination, pregnancy diagnosis results, abortion events, and culling reasons must be recorded consistently and without gaps (Groenendaal et al., 2004; Ptaszyńska, 2023).

Modern herd management software and cloud based systems allow reproductive data to be analyzed together with milk yield, disease records, and feed related information. These systems can generate alerts when selected performance indicators fall below defined thresholds and provide a simple early warning tool. Artificial intelligence based decision support can use large data sets to classify animals into risk groups and indicate which cows are better candidates for synchronization protocols and which can be managed through natural estrus detection (Kamphuis et al., 2010; Ryan et al., 2020; Campos Marques et al., 2024).

3.1.3 Risk Groups and Herd Segmentation

Contemporary program design aims to avoid forcing the entire herd into one protocol. Instead, different strategies are combined for different risk groups in a segmented structure. Separate plans are needed for heifers, high yielding cows with a history of metabolic disease, cows that experienced transition period disorders, and a generally low risk group (Heinrichs et al., 2017; Ribeiro et al., 2013).

In heifers, relatively simple prostaglandin based programs, estrus detection supported protocols, or short 5 day Cosynch programs are often preferred (Fernández Novo et al., 2021). In contrast, cows that experienced ketosis or metritis early in lactation may benefit from more intensive timed artificial insemination strategies such as Double Ovsynch in order to establish pregnancy rapidly and reduce days open in the long term (Souza et al., 2008; Ribeiro et al., 2013).

Segmentation allows expensive and labor intensive protocols to be reserved for subgroups that truly require them. This approach helps control drug costs and improves allocation of labor (Giordano et al., 2011; Wicaksono et al., 2024).

3.2 Classical Synchronization Protocols

The physiological basis of classical synchronization protocols is the control of follicular waves, the luteal phase, and time of ovulation so that a fertile oocyte and a receptive uterus

are present on a predetermined day. Negative energy balance at the beginning of lactation alters luteinizing hormone secretion and progesterone concentrations, which makes physiologically appropriate program design particularly important in early lactation (Butler, 2003; Walsh et al., 2011).

Understanding follicular wave dynamics guides the timing of gonadotropin releasing hormone and prostaglandin administration. The age of the dominant follicle, presence of luteal tissue, and circulating progesterone level change the expected effect of each injection. As a result, the same protocol can lead to different outcomes in different cows.

3.2.1 The Ovsynch Approach and Physiological Background

In the Ovsynch approach, gonadotropin releasing hormone is administered on day 0, prostaglandin F2 alpha is given around day 7, and a second gonadotropin releasing hormone injection follows 2 days later. Timed artificial insemination is then carried out at a fixed interval after the last injection. This scheme decreases reliance on estrus detection and facilitates planning of work routines in large herds (Wiltbank and Pursley, 2014; Fricke and Wiltbank, 2022).

The first gonadotropin releasing hormone injection aims to induce ovulation of the dominant follicle in a large proportion of cows and to initiate a new follicular wave. When the second gonadotropin releasing hormone dose is administered, most cows are expected to be at a similar follicular stage. Prostaglandin induces luteolysis. The final gonadotropin releasing hormone injection then triggers ovulation.

Ovsynch is particularly advantageous in herds with limited labor and large numbers of cows because it does not depend on visual estrus detection. However, if ovulatory response to the first gonadotropin releasing hormone is inadequate or luteolysis is incomplete, pregnancy outcomes are compromised (Bello et al., 2006; Wiltbank et al., 2015).

3.2.2 Presynchronization Protocols and Variants

In the Presynch Ovsynch scheme, prostaglandin injections are administered at set intervals before starting Ovsynch so that more cows enter the protocol at a similar stage of the cycle. This approach improves ovulatory response to the first gonadotropin releasing hormone and increases pregnancy per artificial insemination at timed breeding (El Zarkouny et al., 2004).

Double Ovsynch consists of an Ovsynch type sequence followed by a second Ovsynch that ends with timed artificial insemination. This strategy increases first service fertility and herd pregnancy rate and has been especially effective in high producing herds (Souza et al., 2008; Herlihy et al., 2012; Giordano et al., 2012; Stangaferro et al., 2018).

Protocols such as G6G aim to make presynchronization shorter and more practical by combining prostaglandin and gonadotropin releasing hormone. In multiparous cows, moving a prostaglandin injection to 14 days before presynchronization increased progesterone before insemination and reduced pregnancy loss (Dirandeh et al., 2015). These findings show that not only program length but also the physiological context of each injection is important.

3.2.3 Success of Luteolysis and Prostaglandin Strategies

The success of luteolysis is a critical step in all synchronization programs. A single prostaglandin F2 alpha dose within an Ovsynch protocol does not always achieve complete regression of all corpus luteum tissue. In cows with large or multiple corpora lutea, residual luteal tissue can maintain progesterone concentrations high enough to interfere with ovulation and establishment of pregnancy (Wiltbank et al., 2015; Stevenson et al., 2018).

For this reason, two prostaglandin injections given at a short interval within the same protocol can enhance luteolysis and improve pregnancy outcomes (Wiltbank et al., 2015; Borchardt et al., 2021). Meta analytic evaluations indicate that

a second prostaglandin dose can be economically justified, particularly in high yielding cows and in animals with elevated risk of incomplete luteolysis (Borchardt et al., 2021).

3.2.4 Progestagen Devices and Management of Anestrus

Intravaginal devices that release progestagen are especially useful in anestrus cows and in cows without a functional corpus luteum. These devices create a hormone environment similar to the luteal phase and increase the probability of a synchronized ovulation. Addition of a progesterone device to an Ovsynch type protocol increases pregnancy likelihood in cows without a corpus luteum at the start of treatment (Bisinotto et al., 2015).

Recent studies that incorporated devices such as PRID into modified Ovsynch protocols have reported meaningful improvements in pregnancies per artificial insemination in some herds (Hölper et al., 2023). These results suggest that progesterone support can be a strategic tool in high producing herds where metabolic stress is intense.

3.2.5 Heifers and Short Protocols

In heifers, shorter programs such as the 5 day Cosynch protocol are widely used. These programs achieve strong luteolysis with two prostaglandin doses over a short period and schedule a single timed insemination. Heifers differ from cows in endocrine responsiveness, and high pregnancy rates are achievable. At the same time, small timing errors can reduce success rapidly (Fernández Novo et al., 2021).

Heifer programs therefore need careful attention to body condition, age, body weight, and pubertal status. In heifers with growth retardation, improving feeding and growth strategy usually provides more sustainable benefits than intensifying hormonal protocols alone (Heinrichs et al., 2017).

3.3 Timed Artificial Insemination and Targeted Protocols

Timed artificial insemination is a strategy that reduces reliance on estrus detection and makes reproductive performance more predictable. Under classical estrus detection

schemes, limited observation time, crowded housing, heat stress, and high milk yield can cause a substantial proportion of estrus events to be missed. Timed artificial insemination programs reduce this uncertainty and increase the proportion of cows that receive an insemination (Senger, 1994; Firk et al., 2002; Saint Dizier and Chastant Maillard, 2012).

3.3.1 Targeted Reproductive Management and Risk Based Approaches

Targeted reproductive management avoids a single universal protocol and instead assigns different plans to distinct risk profiles. Cows that experienced post partum metabolic disease, marked loss of body condition, or delayed ovulation are preferentially managed with timed artificial insemination. Cows that are healthy and show regular estrus can be bred based on estrus detection (Walsh et al., 2011; Ribeiro et al., 2013).

Protocols that combine Double Ovsynch for first insemination and early resynchronization increase pregnancy rate particularly in high risk cows (Giordano et al., 2012; Stangaferro et al., 2018). Higher pregnancy rate shortens days open, reduces replacement needs, and lowers the cost of rearing surplus heifers (De Vries, 2006; Wicaksono et al., 2024).

3.3.2 Resynchronization and Control of Time Losses

Timed artificial insemination programs become more effective when they include planned resynchronization. Initiating resynchronization immediately after pregnancy diagnosis shortens the interval to the next insemination in nonpregnant cows and improves pregnancy rate over time (Giordano et al., 2012; Pereira et al., 2013; Lopes et al., 2013).

In some schemes, resynchronization begins about 25 days after the first timed insemination, and pregnancy diagnosis is performed by ultrasound at around 30 to 32 days. Nonpregnant cows continue in the protocol, while treatments are stopped for pregnant cows. This approach minimizes unnecessary hormone

use while limiting time losses in cows that are not pregnant (Pereira et al., 2013; Lopes et al., 2013).

In high risk groups, Double Ovsynch based resynchronization has produced higher pregnancy rates than classical Ovsynch based resynchronization, particularly in high yielding cows with a history of disease (Giordano et al., 2012).

3.3.3 Integration of Sensor Data with Protocols

Combining sensor based estrus detection systems with hormonal programs is an important dimension of targeted program design. Activity monitors, rumination sensors, and milk yield data help identify cows with strong estrus expression and cows with behavior that suggests suppressed estrus (Kamphuis et al., 2010; Cerri et al., 2021).

Cows with clear estrus signals in sensor data can be bred on natural estrus. Cows with weak estrus signals, exposure to heat stress, or metabolic risk can be directed toward timed artificial insemination programs (Ryan et al., 2020; Adenuga et al., 2020). In this way, hormonal protocols and sensor systems function as complementary tools rather than alternatives.

3.4 Comparison of Hormonal and Non-Hormonal Approaches

A central question in reproductive program design is how to balance hormonal timed artificial insemination programs against non hormonal or low hormone approaches based primarily on estrus detection. Non hormonal strategies rely on visual observation, tail paint, activity sensors, and other behavioral indicators of estrus (Firk et al., 2002; Reith and Hoy, 2018; Marques et al., 2020). These approaches reduce drug costs and are perceived by some producers and consumers as more natural.

In herds with high stocking density, limited labor, and heat stress, however, estrus detection efficiency often declines and pregnancy rates become more variable (Lopez et al., 2004; Reith and Hoy, 2018). Suppression of estrus signs is particularly

pronounced in high yielding cows and during hot periods (De Rensis et al., 2017).

Hormone based timed artificial insemination programs reduce pressure on estrus detection and increase the proportion of cows that receive an insemination. Presynchronization combined with Ovsynch, Double Ovsynch, and 5 day Cosynch have all improved first service pregnancy and herd pregnancy rate, and have shortened the time required to achieve pregnancy in many studies (Souza et al., 2008; Herlihy et al., 2012; Wiltbank et al., 2015; Fricke and Wiltbank, 2022). These programs, however, require more drugs, more injections, and more complex scheduling.

3.4.1 Economic Evaluation and Choice by Herd Type

Economic analyses show that the profitability of hormone based programs depends on herd size, estrus detection efficiency, milk price, and labor cost. In large herds where estrus detection is weak, programs that combine presynchronization with Ovsynch tend to outperform strategies that rely mainly on estrus detection (Giordano et al., 2011; Galvão et al., 2013; Wicaksono et al., 2024).

In smaller and medium sized herds, well organized estrus detection combined with simpler programs can be economically adequate. Where sensor technologies are widely used, hybrid models that combine natural estrus breeding with timed artificial insemination are increasingly relevant (Adenuga et al., 2020; Ryan et al., 2020).

Decision support models have quantified the economic impact of different strategies. In a model developed by Giordano and colleagues, herds of 500 cows achieved higher net present value with presynchronization plus Ovsynch than with estrus detection based programs when estrus detection rate fell below 40 percent (Giordano et al., 2011). Simulation studies have shown that when milk price and labor cost are high, programs based heavily on timed artificial insemination tend to be favored, while in smaller herds with well organized estrus

detection, simpler protocols can achieve similar profitability (Galvão et al., 2013).

More recent evaluations suggest that investment in sensors can partly offset hormone costs. In markets where public concern about hormone use is strong, hybrid models that combine sensor systems with targeted and reduced hormone use may represent a rational compromise (Adenuga et al., 2020; Wicaksono et al., 2024). These findings indicate that reproductive program choice must be recalibrated for each herd in light of estrus detection performance, milk price, labor cost, and market expectations.

3.4.2 Welfare, Regulation, and Public Perception

Animal welfare, regulatory constraints, and public perception are also integral to this comparison. European Union legislation has prohibited the use of estradiol for food producing animals and has imposed strict rules on several hormone classes. These regulations have substantially limited the use of classical estradiol based presynchronization schemes, and many countries have adopted protocols that rely on gonadotropin releasing hormone, progesterone releasing devices, and prostaglandin combinations as the standard in practice (EP and Council, 2008; Wiltbank and Pursley, 2014; EU, 2017). Programs that use progesterone devices, gonadotropin releasing hormone, and prostaglandin F2 alpha can be implemented safely within food safety regulations when appropriate withdrawal times and proper recording systems are followed.

Concerns about antimicrobial resistance also encourage a shift from routine antibiotic use toward preventive and selective strategies. This trend supports greater emphasis on calving hygiene, transition period management, and early diagnosis of uterine disease instead of empirical antibiotic treatment, and it increases the importance of preventive components in reproductive program design (Walsh et al., 2011; Ruegg, 2017; Ptaszyńska, 2023).

In organic and low input systems, hormone use may be restricted by regulation or by certification schemes. Under these conditions, estrus detection, sensor technologies, appropriate housing, and feeding strategies become even more critical to maintain acceptable fertility (Reith and Hoy, 2018; Marques et al., 2020). In different market segments, consumer attitudes toward hormone use and specific certification requirements directly shape program selection.

3.5 Clinical Examples

Clinical examples help translate theoretical principles into practical decisions. The following scenarios illustrate reproductive program design under different herd conditions.

Example 1. High Yielding Herd Under Heat Stress

Consider a herd of 300 high yielding cows where pregnancy rates decline markedly during summer and days open increase. Estrus detection is weak because of heat stress and crowded housing. The first intervention is to improve cooling and stocking density. Fans, water sprays, and shading should be used to reduce temperature humidity load in the barn (De Rensis et al., 2017).

In parallel, after the voluntary waiting period, a Double Ovsynch based program can be implemented for first service. High risk cows with metabolic disease can receive additional progesterone support with an intravaginal device, while healthy cows follow a standard Double Ovsynch sequence (Souza et al., 2008; Herlihy et al., 2012; Bisinotto et al., 2015).

Resynchronization that begins immediately after pregnancy diagnosis shortens the interval to the next insemination in nonpregnant cows and limits the cumulative impact of heat stress on fertility (Giordano et al., 2012; Lopes et al., 2013). The goal is to distribute pregnancies more evenly across the year so that losses during hot months are compensated.

Example 2. High Technology Herd with Robotic Milking

In a herd with robotic milking and extensive sensor use, the management system produces daily data on milk yield, milking frequency, activity, and rumination. In such herds, reproductive program design often centers on integrating sensor data with hormonal protocols.

Cows that show strong estrus signals in activity and rumination data can be inseminated on natural estrus. Cows with weak sensor signals, a history of transition disorders, or suspected energy imbalance can enter presynchronization plus Ovsynch or Double Ovsynch based timed insemination programs (Kamphuis et al., 2010; Cerri et al., 2021; Ryan et al., 2020).

Sensor data can also be used to monitor patterns of pregnancy loss by tracking changes in activity and rumination after insemination. Cows with suspected early pregnancy loss can then be prioritized for early resynchronization. This approach increases the precision of hormone use rather than simply increasing drug use.

Example 3. Traditional Herd with Chronic Fertility Problems

In a traditionally managed tie stall herd of moderate size with limited technology, assume that days open are prolonged and the number of inseminations per pregnancy is high. The first step is to review existing records and calculate key indicators such as service interval, first service pregnancy rate, and culling due to infertility (Esslemont and Kossaibati, 2002; De Vries, 2006).

Planned short observation periods at least twice daily, combined with tail paint and simple activity meters, can improve estrus detection (Firk et al., 2002; Marques et al., 2020). Staff training is essential so that estrus signs are interpreted accurately.

For cows in which estrus detection remains poor, a relatively simple timed insemination protocol such as the 5 day Cosynch scheme can be introduced (Fernández Novo et al., 2021). In cows with anestrus or ovarian cysts, progesterone supported protocols and combinations of gonadotropin releasing hormone with prostaglandin can be added as specific modules within the program (Bisinotto et al., 2015; Taktaz et al., 2015; Borş et al., 2018).

In such herds, a gradual implementation strategy is often appropriate. Record keeping and estrus detection are improved first. Timed insemination modules are then introduced for high risk groups. This allows the farm to adapt step by step in terms of both labor and cost.

Example 4. Heifer Management and First Service Strategy

In a herd where heifer management is suboptimal and age at first service is delayed, body weight, body condition score, and growth curves must be assessed first (Heinrichs et al., 2017). Heifers that have reached appropriate weight and maturity can be enrolled in short Cosynch programs followed by timed insemination.

In herds where estrus detection in heifers is difficult, for example on extensive pasture, these short protocols can improve pregnancy rate. In heifers with growth retardation, priority should be given to correcting nutrition and health programs. If hormonal synchronization is applied before physiological maturity, the expected benefit is unlikely to be achieved.

These examples illustrate that reproductive programs are not fixed recipes. They must be tailored to herd conditions, labor structure, record quality, environmental stressors, and available technology. Well designed hormonal protocols that are integrated with estrus detection and sensor systems can support a reproductive management strategy that is both biologically sound and economically sustainable.

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Chapter 4.

ECONOMIC IMPACT OF HORMONAL PROTOCOLS IN DAIRY HERDS

Gaye Bulut¹

Fertility management in dairy herds is no longer a narrow technical exercise focused only on achieving pregnancy. It has become a structured decision area linked to profitability, cash flow stability, and the efficient use of labor and facilities. Hormone based timed artificial insemination programs represent one of the most influential tools in this space. Their value, however, depends on how well they are aligned with herd specific biological risks and managerial realities (De Vries, 2006; Inchaisri et al., 2010; Giordano et al., 2011).

Economic analysis in reproductive management must consider both visible and hidden costs. Visible costs include hormones, veterinary services, labor time devoted to injections and handling, and diagnostic expenditures. Hidden costs are often more influential. They include the opportunity cost of delayed conception, the risk of involuntary culling, and the downstream impact of extended calving intervals on milk income distribution across the year (De Vries, 2006; Inchaisri et al., 2010).

The economic logic of hormonal programs is therefore not simply a question of whether pregnancy rate increases. The relevant question is whether improved reproductive control creates a measurable net return after accounting for herd specific constraints. These constraints may involve labor availability, heat stress burden, housing design, and health

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risks concentrated in early lactation. When these factors are ignored, even biologically effective protocols can yield disappointing financial outcomes (Giordano et al., 2011). This chapter focuses exclusively on the direct economic evaluation of hormonal reproductive protocols.

4.1 Economic Impact of Hormonal Protocols

Hormonal protocols are designed to reduce uncertainty in the timing of insemination and to control time losses between breeding opportunities. Their economic contribution emerges when improved reproductive efficiency translates into measurable changes in milk income, culling dynamics, and replacement needs. The foundational idea is simple. A predictable and higher probability of pregnancy reduces the hidden cost of delay and protects the farm from drifting into the least profitable end of the lactation curve (De Vries, 2006; Lima et al., 2010).

In practice, this predictability has managerial value beyond single cow outcomes. Structured protocols turn reproduction into a scheduled workflow. This reduces reliance on subjective heat detection skills that vary by employee experience, workload, and farm routines. For large herds, the ability to standardize decisions is itself an economic input. It lowers the variance of outcomes and can stabilize monthly cash flow patterns that depend on calving distribution and milk shipment volume (Giordano et al., 2011).

The economic value of fertility improvement can also be misunderstood when farm managers focus only on short term conception metrics. The economic benefit often accumulates through cumulative reductions in days open and through the avoidance of late lactation inefficiency. These are incremental gains that are difficult to visualize without structured record analysis and modeling (De Vries, 2006; Inchaisri et al., 2010).

4.1.1 Revenue Components of Timed Artificial Insemination Programs

The economic impact of TAI programs rests on 2 interrelated pillars. The first is improved pregnancy rate through higher insemination and service rates. The second is the cascade of downstream effects on lactation structure, milk revenue, and involuntary culling. When estrus detection is weak, TAI increases the proportion of eligible cows that actually receive insemination on time. This shifts first service earlier and shortens the interval to reinsemination in nonpregnant cows (Sørensen and Østergaard, 2003; De Vries, 2006; Lima et al., 2010; Giordano et al., 2011; Galvão et al., 2013; Fricke and Wiltbank, 2022).

This mechanism is particularly relevant in systems where estrus expression is biologically suppressed. High producing cows, cows with locomotion issues, and cows experiencing negative energy balance may display weaker behavioral estrus. In these scenarios, reliance on visual detection alone can create an artificial ceiling for service rate. TAI breaks this ceiling by design. It ensures insemination opportunities are not lost to silent estrus or to the logistical reality of limited staff time (Giordano et al., 2011).

Simulation studies consistently show that delaying first insemination reduces annual net return per cow. The mechanism is not only fewer pregnancies. It is also the accumulation of costs during a period of declining milk yield and sometimes increasing health risk. In this sense, TAI programs convert unpredictable reproductive outcomes into a planned and economically legible workflow (Giordano et al., 2011; Fricke and Wiltbank, 2022).

The value of this predictability is likely to be higher in larger herds where labor is a limiting resource and where missed estrus events create measurable time losses. This is one of the reasons why decision support frameworks often identify herd

size as a major modifier of the cost benefit ratio of reproductive programs. A protocol that yields modest gains in a 100 cow herd can generate a more substantial net return in a 1,000 cow herd simply because the managerial and labor savings scale with size (Giordano et al., 2011).

Revenue components should also be interpreted within the broader genetic context. The economic return from earlier and more reliable pregnancy can support faster genetic turnover when farms use advanced semen strategies. Although this chapter does not focus on genetic economics, the link between structured AI scheduling and strategic sire selection is implicitly relevant for long term herd profitability (Lima et al., 2010).

4.1.2 Comparison with Natural Service and Estrus Detection Alone

Natural service can appear attractive in small herds because it reduces dependence on staff time for heat detection and insemination scheduling. Yet it brings its own economic burdens through bull costs, safety risks, and slower genetic progress. Comparative models suggest that TAI often outperforms natural service in herds aiming for structured genetic improvement and controlled replacement decisions (Lima et al., 2010; Giordano et al., 2011).

Bull related costs are not only feed and housing. They also include the risk of injury to workers and the indirect cost of reduced management flexibility. Bulls cannot be deployed selectively for specific risk groups in the same way that hormone programs can be tailored. As a result, natural service may represent a blunt tool in herds that require precise reproductive planning.

Estrus detection only strategies, including those supported by activity monitoring, can narrow the gap. Automated systems may improve detection sensitivity and reduce labor demand. However, their economic performance is highly context dependent. Herd size, estrus intensity, heat stress,

and the early lactation health profile determine whether the investment returns exceed the cost of sensors and subscription infrastructure (Adenuga et al., 2020).

In herds with suppressed estrus expression or high summer fertility losses, systematic TAI can still provide a more stable reproductive output. The key distinction is that sensor based systems improve detection of a biological signal. TAI reduces dependence on the existence of that signal in the first place. This is why a combined strategy may be economically attractive. Sensors can support accurate identification of cows that are cycling normally. TAI can be reserved for cows that fail to express clear estrus or that fall into high risk categories (Giordano et al., 2011; Mottram, 2016; Cerri et al., 2021).

This comparison also highlights the importance of baseline performance auditing. Farms with high natural service efficiency or excellent estrus detection may not experience large marginal gains from universal TAI. In contrast, farms with inconsistent detection performance often see a greater return because TAI reduces inefficiency that was already embedded in daily routines (Galvão et al., 2013).

4.1.3 Program Design, Additional Doses, and the Economics of Fine Tuning

Economic outcomes are shaped not only by the decision to use hormones but also by the architecture of the protocol. Small changes in timing, drug combinations, or the inclusion of additional doses can shift net profitability. One well studied example is the addition of a second prostaglandin F₂α treatment during Ovsynch. Meta analytical assessment combined with stochastic simulation indicates that improved luteolysis can offset the added drug and labor costs in many scenarios, resulting in higher net income per cow (Wiltbank et al., 2015; Borchardt et al., 2021).

This result is economically intuitive. Incomplete luteolysis creates hidden reproductive waste. It leads to failed synchronization, lower conception probability, and a return to

breeding with additional delays. The second prostaglandin dose targets this inefficiency. Its economic value is therefore highest in herds where incomplete luteolysis is more frequent, such as those with a higher proportion of early postpartum cows or cows with compromised ovarian function.

More intensive presynchronization strategies such as Double Ovsynch have also shown consistent improvements in pregnancy per first AI, especially in high producing herds facing measurable health and metabolic risks. Decision support comparisons suggest that these programs are sensitive to milk price and estrus detection performance. Even so, they tend to remain economically competitive in systems where labor constraints and missed breeding opportunities are chronic problems (Giordano et al., 2011).

From a managerial perspective, protocol intensity should be evaluated through a marginal return lens. The question is not whether a program improves pregnancy outcomes. The question is whether the incremental improvement justifies the incremental cost under the farm's specific milk price and labor structure. This is why economic models often emphasize sensitivity analysis. Small changes in milk price or labor cost can shift the ranking of otherwise similar reproductive strategies (Giordano et al., 2011; Inchaisri et al., 2010).

The practical implication is that protocol design should be treated as a modular economic choice. The optimal version is not universal. It is the one that matches the herd's baseline fertility, the distribution of risk cows, and the farm's tolerance for labor intensive routines.

4.1.4 Cow Specific and Risk Based Implementation

A major shift in recent years is the move from blanket hormone use to cow specific targeting. This approach reflects the broader logic of precision livestock farming (Ribeiro et al., 2013; Caixeta and Omontese, 2021; Wicaksono et al., 2024). Hormones are reserved for animals with identifiable risk signals such as prior reproductive failure, low body condition,

or a history of transition disease (Mottram, 2016; Cerri et al., 2021; Campos Marques et al., 2024).

This shift is important because it reframes hormone use as a risk management tool rather than a universal default. In economic terms, it aims to concentrate resources where the probability of marginal gain is highest. Cows with greater risk of reproductive failure under routine management are the logical targets for more intensive intervention. This can improve herd level outcomes while simultaneously reducing overall drug expenditure.

Recent economic evaluation of cow based reproductive management programs found that selective hormone use in problem cows can improve net profitability compared with applying a uniform protocol across the entire herd. Drug use declines while reproductive performance in high risk groups is preserved (Wicaksono et al., 2024). This result supports the argument that the economics of reproduction are increasingly data driven.

This strategy also reduces the risk of over intervention. It allows clinicians to place hormone use within a more defensible economic rationale. Activity monitoring, clinical scoring, and structured record analysis can help identify these risk groups earlier and with higher accuracy (Mottram, 2016; Cerri et al., 2021). The economic logic is straightforward. If the marginal benefit of a hormone protocol is highest in cows with the greatest probability of failure under routine management, then targeting is likely to improve both biological efficiency and cost effectiveness.

4.2 Synthesis of Economic Drivers

The economic impact of hormonal protocols is not a single number. It is an interaction between herd size, baseline estrus detection performance, transition health burden, milk price, labor cost, and the discipline of implementation. Across most modeling frameworks, the strongest economic benefits appear in medium and large herds with suboptimal estrus detection

and significant organizational complexity (De Vries, 2006; Lima et al., 2010; Giordano et al., 2011).

At the same time, hormones should not be treated as a substitute for proper metabolic and environmental management. When negative energy balance, lameness, or postpartum disease are common and unresolved, the expected return on hormonal investment decreases. In such herds, the economic priority may need to shift toward correcting upstream health and housing factors before expanding protocol intensity (Ribeiro et al., 2013; Caixeta and Omontese, 2021).

Economic decision support systems address this complexity by allowing farms to compare program strategies under different assumptions. These models emphasize that the most profitable program is not always the most hormonally intensive one. It is the program that achieves the best balance between pregnancy outcomes, implementation feasibility, and cost exposure within the farm's specific operational limits (Giordano et al., 2011).

In summary, hormonal reproductive protocols can generate meaningful economic value. This value is driven by improved service rate, reduced reproductive delay, and greater predictability. The magnitude of return depends on herd context. It also depends on whether farms treat protocol choice as a strategic economic decision rather than a habit.

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Chapter 5.

REPRODUCTIVE DYNAMICS AND HERD STRUCTURE IN DAIRY COWS

Enes Çerçi¹

Fertility management in modern dairy systems is increasingly evaluated through long term herd structure and economic resilience rather than short term pregnancy outcomes alone. This perspective aligns with the framework introduced at the end of your previous chapter, where days open, dry period length, replacement rate, and transition health were positioned as interdependent drivers of profitability and sustainability. This chapter, expands this lens and treats these variables as a single management system that shapes the biological rhythm and financial stability of the herd.

The core argument of this chapter is simple. Reproductive performance is not only a question of whether cows become pregnant. It is also a question of when pregnancies occur, how consistently calving events can be planned, and how many productive lactations can be achieved before involuntary exit. When these outcomes are stable, farms can manage feed allocation, labor, and capital with less volatility. When they are unstable, even technically sound breeding programs may become economically fragile (De Vries, 2006; Inchaisri et al., 2010; Giordano et al., 2011).

5.1 Days Open and Lactation Economics

Days open is one of the most influential indicators linking reproduction to farm economics. It represents the time cost of remaining non pregnant after the voluntary waiting period.

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Each additional day open extends the interval between profitable reproductive events and shifts a cow further into late lactation, where marginal milk income often declines relative to daily maintenance costs (Sørensen and Østergaard, 2003; De Vries, 2006). The concept is biological, but its consequences are managerial and financial.

A crucial point often missed in field discussions is that the economic effect of days open is not uniform across herds. The cost of delay depends on milk price, feed cost, reproductive culling policy, and the availability of replacement heifers. In some scenarios, especially when milk price is high and replacement pressure is low, the immediate penalty per day may appear modest. However, the structural impact on herd distribution across lactation stages can still be substantial. This is why decision support models typically treat days open as a system level variable rather than a single cow outcome (Inchaisri et al., 2010; Giordano et al., 2011).

5.1.1 The Economic Meaning of Delayed First Insemination

Earlier modeling work showed that postponing first insemination reduces annual net return per cow through both direct and indirect pathways. The most visible pathway is a lower pregnancy rate. The less visible pathway is the accumulation of costs during a period when milk yield may be declining and health risks can rise (Sørensen and Østergaard, 2003; De Vries, 2006). This distinction matters because it explains why farms with good genetics and high milk yield can still suffer considerable financial losses from weak reproductive timing.

Extended calving intervals may sometimes increase milk per lactation, but this does not guarantee higher profitability. The farm still carries a prolonged period of feed, housing, and labor expenditure before the next calving cycle begins (Arbel et al., 2001). This reinforces the idea that total milk yield per lactation is an incomplete indicator of reproductive success when the economic goal is stable annual performance.

5.1.2 Lactation Curve Dynamics and Herd Level Planning

The relationship between days open and the lactation curve is central to understanding long term profitability. Early lactation and peak production generate high revenue density. Late lactation milk may remain valuable, but its marginal economic advantage narrows when daily maintenance costs and the opportunity cost of delayed calving are considered (De Vries, 2006). When many cows drift into prolonged late lactation due to fertility failure, the herd level lactation profile becomes less efficient.

This structural drift also complicates ration design. Farms may need to maintain larger late lactation groups and adjust energy density across more heterogeneous stages. Over time, such complexity can increase feed waste and raise the risk of mismatched nutrition. The reproductive issue therefore becomes a nutritional and operational issue. Economic models that integrate feeding and reproduction have repeatedly highlighted this system wide cost of delay (Inchaisri et al., 2010).

5.1.3 Strategic Targets for Days Open

The practical goal is not to minimize days open at any cost. The goal is to identify a biologically realistic and economically optimal target. Attempts to push insemination too early in cows that are still recovering from negative energy balance or disease may increase intervention intensity and reduce overall efficiency (Butler, 2003; Walsh et al., 2011). This is why modern herd strategies emphasize balancing reproductive ambition with transition health stability.

Automated heat detection systems can improve this balance by increasing insemination rate without necessarily increasing hormonal intervention intensity. However, their economic viability depends on herd size, infrastructure cost, and estrus expression sensitivity (Adenuga et al., 2020). In high producing herds where estrus behavior can be suppressed by metabolic

stress or heat stress, these tools may need to be integrated with structured reproductive programs to maintain stable outcomes.

5.2 Dry Period Length and Reproductive Efficiency

Dry period length is often discussed primarily through its effect on subsequent milk yield. Its reproductive relevance is equally important. A predictable dry period requires timely conception. It also supports controlled body condition dynamics and improves the metabolic readiness that underpins early lactation fertility (Cardoso et al., 2013; Caixeta and Omontese, 2021). The dry period is therefore not only a milk management phase but also a fertility enabling phase.

5.2.1 Metabolic Trade Offs of Shorter or Longer Dry Periods

Very short dry periods can limit mammary tissue regeneration and reduce milk yield in the next lactation. Very long dry periods can increase non productive days and promote excessive body condition gain. This gain increases the risk of ketosis, fatty liver, and poor immune function after calving (Cardoso et al., 2013; Caixeta and Omontese, 2021). From a fertility perspective, these disorders are not side notes. They are causal drivers of delayed cyclicity and poor conception outcomes.

The practical implication is that dry period decisions should be guided by herd risk profiling. Herds with high rates of overconditioned cows or recurring ketosis may need stricter control of dry period nutrition and length. Herds with excellent metabolic stability may explore modest adjustments to reduce non productive time. The relevant question is not whether a shorter or longer dry period is universally superior. The relevant question is how the dry period interacts with the specific metabolic and housing environment of the farm.

5.2.2 The Role of Heat Stress and Cooling Strategies

Dry cows are sometimes managed in facilities that receive less attention for heat abatement. This is an expensive oversight.

Economic evaluation across different regions suggests that cooling dry cows can be financially feasible because it reduces postpartum disease and improves subsequent milk yield and fertility (Ferreira et al., 2016). The logic is consistent with the broader reproductive economics narrative. Upstream stability protects downstream reproductive efficiency.

Heat stress also reduces estrus expression, which indirectly increases days open by lowering insemination rate. Therefore, the economic return of cooling may be amplified when farms rely heavily on estrus detection rather than systematic synchronization (De Rensis et al., 2017; Sammad et al., 2020). This point reinforces the need to evaluate environmental investment and reproductive strategy as a combined system.

5.2.3 Dry Period Length as a Planning Tool

The dry period can be used as a managerial anchor for herd structure. When conception occurs within a predictable window, dry off and calving schedules become more stable. This allows more precise ration formulation and reduces the risk of abrupt group changes. In seasonal or pasture based systems, this stability is even more critical because the cost of missing a calving window can be disproportionately high (Ribeiro et al., 2013).

In intensively housed herds, the challenge is often organizational rather than seasonal. A shift in dry off dates can disrupt stall allocation, pen flow, and labor routines. This can create cascading inefficiencies that extend beyond the individual cow. For this reason, decision models often treat dry period length and days open as linked levers of herd level efficiency (Overton and Dhuyvetter, 2020).

5.3 Replacement Rate and Longevity

Replacement rate reflects how quickly cows exit and are replaced by heifers. The simplicity of the indicator hides a complex economic reality. Raising a replacement heifer requires significant investment. The animal consumes

resources for months before producing milk. Therefore, high replacement rates can erode profitability even when genetic progress appears to improve average performance.

Your previous chapter already emphasized that excessive replacement frequently signals economic inefficiency and that infertility is a major driver of premature exit (refer Chapter 4). This chapter expands this theme by connecting replacement decisions to long horizon fertility management.

5.3.1 Economic Weight of Replacement Inventory

Overton and Dhuyvetter showed that raising more heifers than needed can create a silent but substantial cost burden. This may be masked in periods of high milk price or rapid expansion but becomes visible when cash flow tightens (Overton and Dhuyvetter, 2020). Comprehensive heifer research reviews also emphasize that the pre calving period is a major cost center in modern dairy systems, which increases the economic value of retaining healthy, fertile cows for more lactations (Heinrichs et al., 2017).

Replacement availability also shapes reproductive risk tolerance. When heifers are abundant, farms may cull infertile cows earlier. When heifer supply is limited or expensive, retaining marginal cows may be economically rational. Models that integrate these input constraints show that optimal replacement and breeding decisions vary widely across herds and markets (Groenendaal et al., 2004).

5.3.2 Fertility Driven Longevity and Genetic Trade Offs

Fertility is one of the most important determinants of functional longevity. Cows that fail to conceive on time are often culled even when milk production is adequate. Improving conception timing therefore protects both milk income and the investment already embedded in mature cows. From this viewpoint, fertility improvement is a longevity strategy as much as a pregnancy strategy. Additionally, there is an economic link between faster genetic improvement and longer productive life. Rapid turnover can increase the average genetic value.

Furthermore, it can also increase total replacement costs in the event of increased involuntary culling. This situation lies at the heart of modern herd economics and must be explicitly acknowledged in breeding planning (De Vries, 2017).

5.3.3 Sustainability Dimensions of Replacement Control

Replacement management increasingly carries environmental relevance. Heifer rearing generates emissions during a period when no milk is produced. Therefore, preventing avoidable culling through improved fertility can reduce greenhouse gas emissions per unit of lifetime milk (Garnsworthy, 2019). The economic and environmental incentives therefore converge in favor of stable reproductive performance and rational replacement targets.

This convergence also supports a more defensible narrative for selective reproductive interventions. Targeted strategies that preserve fertility in higher risk cows can reduce unnecessary herd wide interventions while preventing replacement inflation. This approach is consistent with emerging evidence that systematic yet selective hormone use can improve net profitability in problem groups (Wicaksono et al., 2024).

5.4 Transition Health and the Intersection of Fertility and Economics

The transition period is the metabolic foundation of the next reproductive cycle. A cow entering early lactation with severe negative energy balance, inflammation, or lameness is unlikely to achieve timely conception regardless of the reproductive strategy. This is not an optional add on to fertility management. It is an economic prerequisite.

The mechanistic link between energy balance and fertility remains robust. Negative energy balance impairs follicular development, delays ovulation, and reduces conception probability (Butler, 2003). Clinical reviews also document the reproductive impact of uterine disease, lameness, and systemic inflammatory conditions (LeBlanc, 2008; Walsh et al., 2011). These disorders lengthen days open and increase the probability

of infertility culling, creating a direct bridge between the biological and financial levels of herd performance.

5.4.1 Hidden Costs of Transition Disorders

Transition disorders generate direct treatment costs. Their larger economic impact often emerges indirectly through milk loss, prolonged days open, and early exit. The metabolic indicators around calving are associated with later disease risk and performance, reinforcing the value of early risk identification for economic planning (Chapinal et al., 2012).

This evidence supports a layered management approach. Farms should prioritize prevention or early correction of transition disorders before intensifying reproductive interventions. This principle by noting that hormonal or technological tools cannot fully compensate for unresolved upstream health problems (Refer Chapter 4).

5.4.2 Risk Segmentation and Program Assignment

A stratified approach is becoming the practical standard in advanced herds. Cows are classified based on transition health signals, body condition dynamics, previous reproductive history, and sensor derived behavior. Low risk cows can be managed with robust estrus detection based insemination. Higher risk cows can be directed to structured synchronization or more disciplined resynchronization. The benefits of this approach are both economic and ethical. It increases efficiency by allocating interventions where marginal returns are highest (Giordano et al., 2011; Mottram, 2016; Campos Marques et al., 2024; Wicaksono et al., 2024).

Predictive modelling studies that use behavioral sensor data and on farm records to identify pregnancy risk provide an emerging data base for this kind of segmentation (Barden et al., 2024; Campos Marques et al., 2024). As machine learning frameworks mature, the economic value of risk based assignment may become more measurable and more transferable across herd types (Ryan et al., 2020; Grzesiak et al., 2025).

5.4.3 Heat Stress

Heat stress amplifies many transition risks and reduces reproductive efficiency through suppressed estrus expression and impaired embryo survival (De Rensis et al., 2017; Sammad et al., 2020; Rhoads, 2023). When heat stress overlaps with early lactation, the risk of delayed cyclicity and extended days open increases. In such contexts, the economic priority may shift toward environmental mitigation and nutritional support before further intensifying reproductive protocols (De Rensis et al., 2017; Roth, 2020; Rhoads, 2023).

This layered reasoning does not weaken the rationale for structured reproductive programs. Instead, it strengthens it by placing such programs within a realistic biological foundation. The most effective fertility strategy under heat stress is rarely a single tool. It is a coordinated package that integrates cooling, nutrition, detection, and selective synchronization.

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CONCLUSION

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The data and discussions presented in this book show that fertility in dairy herds cannot be reduced to the single goal of increasing pregnancy rate. Fertility management is a complex process with biological, environmental, digital, economic and ethical dimensions, and the book proposes a holistic framework for modern herd management by addressing these dimensions together. A successful fertility program is not limited to regulation of the ovarian cycle but also requires appropriate energy balance, uterine health, infection control, management of environmental stress, robust data infrastructure and decision processes that comply with relevant regulations (Walsh et al., 2011; De Rensis et al., 2017; De Vries, 2017).

At the biological level, the first chapter of the book examined in detail the critical importance of the postpartum period. Negative energy balance, ketosis and fatty liver, together with uterine diseases such as metritis and endometritis, play a decisive role in the interval to first service and in early embryonic loss (Butler, 2003; LeBlanc, 2008). Many years of genetic selection with an exclusive focus on milk yield have created an unfavorable relationship between high production and fertility. Selection indexes that include reproductive traits have partly mitigated this antagonism (Pryce and Veerkamp, 2001; Kgari et al., 2020). Heifer rearing strategies and early life losses form another critical link for the sustainability of the herd inventory of productive females (Heinrichs et al., 2017).

Findings on environmental and management factors show clearly the impact of heat stress and housing conditions on fertility. When the temperature humidity index exceeds specific thresholds, there is a consistent negative association

with feed intake, milk yield and conception rate (Al Katanani et al., 2002; Morton et al., 2007). Planning ventilation, fan and water spray systems and appropriate stocking density together is a basic management tool for both animal welfare and fertility performance (Kadzere et al., 2002; Becker et al., 2020). Within this framework environmental management should be viewed not as a tool that compensates for inadequate hormone programs but as a preventive strategy that works alongside them.

Digital monitoring systems and artificial intelligence based analytics are framed in this book not as a marginal addition to classical fertility management but as an infrastructure placed at the center of decision making. The combination of sensor streams such as activity, rumination, body temperature, milk yield and milk composition with herd records provides high sensitivity for estrus detection and prediction of pregnancy probability (Neves et al., 2012; Pereira et al., 2020; Campos Marques et al., 2024). Machine learning models developed for transition period disorders such as metritis and disorders of energy balance make it possible to identify high risk cows before clinical signs become evident (Džermeikaitė et al., 2025). Despite this potential, data integrity, sensor maintenance requirements, model generalizability and the ability of field users to interpret model outputs remain key constraints on the success of digital systems (Grzesiak et al., 2025).

Hormone based timed artificial insemination programs are discussed throughout the book from both clinical and economic perspectives. Ovsynch and related protocols can substantially increase pregnancy rate and shorten days open in herds with weak estrus detection (Wiltbank and Pursley, 2014; Wiltbank et al., 2015). Economic models indicate that these programs can increase net profit, especially in large and high producing herds, but also show that outcomes vary considerably with milk price, hormone costs, labor conditions and herd structure (De Vries, 2006; Wicaksono et al., 2024). Evaluation of hormone use must include not only the direct reproductive effect but also

residue risks for human health, regulatory limits and public perception. Risk based assessment principles and the guidance of international authorities should therefore be considered together (WHO and FAO, 2009; 2024; Evans et al., 2022).

A central theme that emerges in this book is that sustainable fertility management is not a narrow technical optimization problem. Long term success requires that economic, environmental and ethical dimensions be considered simultaneously. From the perspective of economic sustainability, shorter days open, a lower involuntary replacement rate and a greater number of lactations per cow are associated with higher lifetime milk yield per animal. This pattern increases productivity per cow and reduces the number of nonproductive animals in the herd, which improves overall use of resources. A lower need to rear surplus heifers prevents tying up capital in nonproductive animals and allows working capital to be reallocated to more efficient uses within the enterprise (Inchaisri et al., 2010; Giordano, 2019; Overton and Dhuyvetter, 2020).

From an environmental sustainability standpoint, fertility management has the potential to reduce greenhouse gas emissions per unit of product by allowing the same volume of milk to be produced with fewer animals and shorter nonproductive periods (Garnsworthy, 2019). In this context, improved fertility does not only mean better reproductive performance, it also becomes part of the strategy to mitigate climate change. Effective management of heat stress, improvement of housing and cooling systems and optimization of resource use reduce the physiological burden on cows and help limit environmental pressure. Given that climate change is expected to alter patterns of temperature and humidity in the coming years, the importance of such adaptation strategies will increase further.

Animal welfare and public trust constitute the third main dimension of sustainable fertility management. Appropriate

housing, adequate lying space, non slippery floors, procedures that minimize pain and stress during interventions and early diagnosis of transition period diseases, together with the reduction of unnecessary treatments, raise welfare standards (WOAH, 2014; 2016). This welfare oriented approach supports productive performance and aligns the production model with societal expectations regarding the ethics of animal sourced foods. Transparent, traceable and regulation compliant management of hormone use and digital monitoring systems is critical for maintaining consumer confidence (Evans et al., 2022). From this perspective fertility management is not only a technical production tool but also a strategic field in relation to food safety, public health and social acceptability.

The future research agenda that follows from the topics discussed in this book can be organized around three main axes. The first is the integration of data from different types of sensors and the use of explainable artificial intelligence methods to make estrus detection and health risk prediction more transparent and more generalizable across herds and systems (Grzesiak et al., 2025). The second is the development of low cost and scalable fertility management packages that can be adapted to different climatic zones and production systems. The third is the creation of interoperable databases at national and regional level that combine milk recording systems, health data and reproductive records and that can be used as a foundation for both research and decision support tools (Garnsworthy, 2019).

In summary, fertility management in dairy cattle requires a systems based perspective that takes into account biological mechanisms, environmental conditions, digital technologies and economic constraints at the same time. This book aims to make such a perspective concrete and usable for clinicians and decision makers. In the long run the goal is to support herds that are healthier and longer lived, production systems that are more resilient in economic and environmental terms and a

society that has confidence in the dairy food chain. Achieving this goal will depend on interdisciplinary collaboration, a culture of data driven management and continuous education as essential elements in the coming period.

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