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## Dipartimento di Medicina Veterinaria e Produzioni Animali

MASTER'S DEGREE IN PRECISION LIVESTOCK FARMING (PLF)

Experimental Thesis

in

"Production Process Control"

# " DEVELOPING AN AUTONOMOUS DECISION-MAKING SUPPORT SYSTEM USING BEHAVIOURAL, PRODUCTIVE AND METEOROLOGICAL DATA FROM A DAIRY CATTLE FARM IN SPAIN"


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# ABSTRACT

*This study presents a novel approach to mitigating heat stress in dairy cows through the development and application of a data-driven linear model, designed to optimize the use of shower cooling systems. Recognizing heat stress as a significant detriment to dairy cow welfare and milk production efficiency, our research leverages extensive behavioral and environmental data to construct a predictive model that accounts for variables such as Temperature-Humidity Index (THI), rumination, ingestion, and panting behaviors, milk production and feed consumption data.*

*Utilizing a comprehensive dataset collected from a dairy operation, we employed linear regression analysis to elucidate the intricate relationships between these variables and their collective impact on panting behavior, an immediate indicator of heat stress. The predictive prowess of our model enabled the formulation of a personalized shower plan, which, when tested, demonstrated a significant reduction in panting scores from a mean of 17.44 to 8.00, achieving a reduction in heat stress manifestation by approximately 90.42%.*

*Despite facing challenges such as the requirement for high-performance computing to process large datasets and the critical evaluation of multivariable interactions and data quality, our findings highlight the potential of integrating predictive algorithms into current dairy farm management software and sensor technologies. Moreover, the study underscores the need for further exploration into more sophisticated modeling techniques, such as neural networks and random forests, to enhance the predictive accuracy and applicability of heat stress mitigation strategies.*

*In conclusion, our research contributes to the growing body of knowledge on precision livestock farming by showing the viability of data-driven interventions in addressing heat stress. The successful implementation of our model not only promises to improve animal welfare and operational efficiency but also serves as a testament to the potential of technology and data analytics in fostering sustainable dairy farming practices in the face of climatic challenges.*



*Keywords: Heat stress, Dairy cows, Predictive model, Shower cooling systems, Temperature-Humidity Index (THI), Animal behavior, Data-driven interventions, Precision livestock farming, Milk production efficiency, Sustainable dairy farming practices*

# CHAPTER 1: LIVESTOCK MANAGEMENT AND TECHNOLOGICAL ADVANCEMENTS

Livestock management stands as a pivotal cornerstone within the realm of global agriculture, underpinning the very essence of food security, economic stability, and the livelihoods for billions of people. In a world where the balance between human nutritional needs and sustainable environmental practices is increasingly delicate, the role of sophisticated livestock management cannot be overstated (P.K.Thornton, 2010).

This field, rich in tradition yet dynamic in its evolution, encapsulates the collective efforts to nurture, protect, and optimize the health and productivity of animals that are crucial to our food systems. As we stand at the precipice of a future marked by burgeoning populations (United Nations, 2022) and shifting dietary preferences (Vermeulen *et al.* 2020), the strategic importance of livestock management in bolstering food security is more pronounced than ever.

Globally, livestock serves not just as a source of essential nutrition through the provision of meat, milk, and eggs, but also plays a vital role in the socio-economic fabric of rural communities. It offers a pathway to poverty alleviation, economic resilience, and the empowerment of marginalized populations, including a significant proportion of women in agriculture. The intricate symbiosis between humans and livestock, honed over millennia, has fostered diverse farming practices, each adapted to the unique environmental and cultural landscapes of regions across the world (M. Upton. 2010). Yet, this deeply rooted dependence underscores the need for robust management practices that can address the multifaceted challenges of today's agricultural landscape.

The advent of technological advancements has ushered in a new era for livestock management. Innovations in sensor technologies, data analytics, and precision farming techniques have transformed traditional practices, enabling farmers to monitor animal health and behaviour with unprecedented accuracy. These technologies offer the promise of optimizing resource use, enhancing animal welfare, and minimizing the environmental footprint of livestock production (J.Schillings *et al.* 2021).

In an age where climate change poses one of the greatest threats to agricultural sustainability and food security, the ability to harness data for informed decision-making is indispensable (EU, 2023). It empowers farmers to navigate the complexities of modern agriculture, from managing the risks of disease outbreaks to addressing the nutritional needs of herds, thereby ensuring the resilience of food systems against the caprices of a changing climate.

However, the potential of livestock management extends beyond the mere adoption of technologies. It encompasses the holistic understanding of animal welfare, the ethical stewardship of natural resources, and the pursuit of practices that align with the principles of sustainability.

As the global community grapples with the challenges of feeding a projected population of nearly 10 billion by 2050, (Van Dijk *et al.*, 2021) the imperative to adopt sustainable livestock management practices becomes increasingly urgent. These practices not only aim to meet the immediate nutritional demands but also safeguard the environment for future generations. The integration of sustainable feed sources, efficient water use, and the reduction of greenhouse gas emissions are among the myriad strategies that underscore the multifaceted approach required in contemporary livestock management (FAO, 2010).

The significance of livestock management in global agriculture and food security is thus multifaceted, reflecting its role in nutritional provision, economic stability, and environmental sustainability. As we advance, the continued innovation in livestock management practices will be critical in addressing the dual challenges of ensuring food security and mitigating environmental impacts. The journey toward sustainable livestock management is complex and fraught with challenges, yet it remains one of the most promising pathways to achieving a balance between human needs and environmental stewardship.

In light of these considerations, the pursuit of advanced livestock management practices is not merely an option but a necessity. The development and implementation of data-driven decision support systems, as investigated in this thesis, represent a pivotal step forward in this journey. By optimizing the management of heat stress in dairy cows through technological innovations, this research contributes to the broader goal of enhancing livestock productivity and welfare in harmony with the environment. It underscores the evolving nature of livestock management as a field that is not only rooted in tradition but also propelled forward by innovation, in the relentless pursuit of global food security and sustainability.

## 1.1. History and evolution of livestock management practices

The history of livestock management is as old as human civilization itself. It has evolved over millennia, transitioning from rudimentary herding practices to sophisticated, technology-driven strategies. This journey from the past to the present of livestock management mirrors the broader trajectory of human development and underscores the critical role animals have played in shaping societies.

In the early days of domestication, livestock management was primarily about survival. Domesticating animals such as cattle, sheep, goats, and pigs provided early humans with a reliable food source, which was a significant step up from the uncertainties of hunting and gathering. As civilizations began to form, these animals also became vital for labour, clothing, and transportation. This transition marked the first revolution in agriculture and set the stage for more stable human settlements.

As societies advanced, the significance of livestock management grew. During the agricultural revolution, it wasn't just about managing animals for immediate needs. Historical analysis shows that this occurred particularly when humans perceived domesticated animals from yielding direct benefits to a broad complete understanding. They made the new domestic animal as an object of medicine: animals were refashioned into tools and targets of disease investigation, regulation, and management (H. Kean, P. Howell, 2018). It became a science of breeding, nourishing, and caring for animals to maximize their output and efficiency. Selective breeding practices emerged, emphasizing desirable traits like milk yield in cows or wool quality in sheep. Such innovations were crucial in boosting agricultural productivity and supporting burgeoning populations.

The industrial revolution brought further transformations. Mechanization reduced the reliance on animals for labour, shifting the focus of livestock management towards optimizing meat, dairy, and wool production. The developement of veterinary science played a pivotal role in this era, improving animal health and thereby their productivity (J.H. Carag *et al.* 2021).

In recent times, the field of livestock management has been revolutionized by technology. Precision livestock farming, which uses data analytics, IoT, Internet of Things, devices, and AI, Artificial Intelligence, has led to more efficient and humane practices. Modern techniques like GPS tracking, automated feeding systems, and health monitoring through wearable technology have not only improved farm efficiency but also animal welfare (J. Carolin *et al*. 2017). This is particularly relevant in the context of increasing concerns about ethical animal treatment and sustainable practices. Despite these advancements, the sector faces new challenges. The global demand for animal products is rising, as well as concerns about the environmental impact of livestock farming. Issues like methane emissions from cattle, deforestation for grazing, and the overuse of antibiotics present complex problems that require innovative solutions (J. Carolin et al. 2017). Moreover, climate change has introduced new variables into the equation. Fluctuating weather patterns, increasing incidents of droughts and floods, and emerging animal diseases have made livestock management more challenging. Adapting to these changes while ensuring food security and sustainability is one of the key challenges for the field today (C. Calvosa *et.al*).

Therefore, livestock management is not just a story of human progress, but a narrative deeply intertwined with the challenges and aspirations of today's civilization. From ensuring survival to enhancing efficiency and sustainability, this field reflects our evolving relationship with nature and technology. As we move forward, the focus is shifting towards balancing productivity with sustainability. The future of livestock management will likely be marked by further technological advancements, but these must be harmoniously integrated with environmental stewardship and ethical considerations (FAO, 2017). This dynamic field continues to be ripe for exploration, innovation, and scholarly discussion, promising exciting opportunities for research and development.

## 1.2. Advancements in sensor technologies in livestock management

The landscape of livestock management has undergone a profound transformation, transitioning from age-old practices rooted in manual observation and intuition to the data-driven precision of modern farming. This evolution has been significantly propelled by advancements in sensor technologies, marking a new era where efficiency, productivity, and animal welfare are enhanced through innovation.

Historically, livestock management was predominantly guided by the accumulated wisdom of generations, with decisions based on observable behavior and physical signs. While these methods have their merits, they are inherently limited by the scope of human observation and the latency in decision-making (Birch B. , 2023).

The advent of sensor technologies has revolutionized this traditional landscape, introducing precision livestock farming (PLF) as a cornerstone of modern agricultural practices. PLF harnesses the power of real-time data collection, enabling a nuanced understanding of individual and herd-level dynamics that were previously unattainable (L. Tedeschi *et al.* 2021). This shift from empirical to evidence-based management represents a paradigm change, significantly impacting the way livestock are monitored, managed, and cared for.

Sensor technologies in livestock management encompass an array of devices designed to monitor various aspects of animal health, behaviour, and environment. These technologies play a pivotal role in the daily management and strategic decision-making processes on farms. By providing continuous, real-time data, sensors empower farmers to make informed decisions swiftly, enhancing animal welfare and optimizing farm operations. (L. Tedeschi et al. 2021) The integration of sensor data into decision-making processes exemplifies a proactive approach to management, where potential issues can be addressed before they escalate, and resources can be allocated more efficiently.

### 1.2.1 Types of sensors technologies and their applications in livestock farming

Sensor technologies in livestock farming can be categorized based on their application areas: health monitoring, environmental control, feeding management, and reproductive monitoring. Each category serves a distinct purpose, contributing to the holistic management of livestock farms, as summarized in the following:

- **Health Monitoring Sensors**: wearable sensors attached to animals, such as ear tags, collars, and leg bands, provide invaluable data on vital signs (heart rate, body temperature), activity levels (movement, lying time), and behaviours indicative of health status (rumination, ingestion, panting). These sensors enable early detection of illnesses, allowing for timely intervention and reducing the need for broad-spectrum antibiotic treatments.
- **Environmental Sensors**: these sensors monitor the conditions within barns or grazing fields, measuring parameters like temperature, humidity, and air quality. The data collected helps in managing the microclimate to ensure it remains within optimal ranges for animal comfort and health, directly influencing productivity and welfare.
- **Feeding Management Sensors**: technologies deployed in automated feeding systems and milk parlours collect data on feed intake, milk yield, and milk composition. This information is crucial for customizing feeding strategies to meet the nutritional needs of individual animals or groups, optimizing growth, and lactation performance.
- **Reproductive Monitoring Sensors**: sensors designed to detect oestrus and monitor reproductive health play a critical role in breeding management. By accurately predicting ovulation times, these technologies improve breeding efficiency and success rates, directly impacting farm productivity.

The application of these sensor technologies in livestock farming underscores a significant move towards individualized animal management. By treating animals as individuals, with unique health, nutritional, and comfort needs, PLF elevates the standards of care and management practices. The implementation of sensor technologies in livestock management has demonstrated substantial benefits, including improved animal welfare, increased operational efficiency, and enhanced productivity. These technologies facilitate a deeper understanding of animal needs and farm dynamics, enabling more precise and responsive management practices (Rana *et al.* 2023).

## 1.3. The role of data in livestock management

Following the historical trajectory of livestock management, the recent chapter in this evolutionary tale is marked by the advent and integration of data analytics and technology. The significant role that data plays in modern livestock management cannot be overstated, as it encapsulates the shift from traditional, intuition-based practices to precision and evidence-based decision-making processes.

In contemporary livestock management, data serves as the linchpin that connects various aspects of animal husbandry. This transition to a data-centric approach represents a paradigm shift in how livestock are cared for and managed. The emergence of PLF is a testament to this change. PLF employs a range of technologies to continuously monitor and collect data on animal health, behaviour, and environment. This constant stream of data offers unprecedented insights into the well-being and productivity of each animal, allowing for timely interventions and personalized care (Suresh Neethirajan, 2020).

The implications of this data-driven approach are profound. For instance, by analysing patterns in eating behaviour or movement, farmers can swiftly identify health issues, often before physical symptoms manifest. This early detection not only improves animal welfare but also reduces the economic losses associated with disease. Similarly, data on milk yield and quality can inform breeding decisions, leading to genetic improvements across herds. Moreover, data analytics in livestock management extends beyond individual animal care. It encompasses resource optimization and environmental management, critical in the context of sustainable farming practices. For example, data on feed consumption and conversion rates helps optimize feeding strategies, reducing waste and lowering costs. In terms of environmental sustainability, data on livestock emissions contributes to more informed strategies to mitigate the ecological footprint of farming activities. (Kaledio P, Russell E, 2023).

The role of data also extends to regulatory compliance and traceability, increasingly important in a world focused on food safety and ethical production. Data systems can track the lineage of animals, their health history, and the treatments they have received, ensuring transparency and quality assurance from farm to table (Kaledio P, Russell E, 2023).

Despite the clear benefits, the integration of data in livestock management is not without challenges. The sheer volume and variety of data can be overwhelming, requiring sophisticated tools for analysis and interpretation. Additionally, the digital divide remains a concern, with access to advanced technologies often limited to larger, more affluent farms, potentially widening the gap between small and large-scale operations (Kaledio P, Russell E, 2023).

Within the state of the art, the role of data in livestock management represents the convergence of agriculture with digital technology, opening new frontiers for efficiency, sustainability, and animal welfare. As we venture more further into the 21st century, the continue evolution of this field will likely hinge on the innovative use of data, requiring continuous research, development, and adaptation. The potential for further advancements in this specific area is vast, promising an upcoming future where livestock management is not only more efficient but also more attuned to the needs of animals and the environment. This future, built on the foundation of data, holds the promise of transforming livestock management into a more precise, humane, and, more importantly, sustainable practice.

## 1.4. Heat stress in dairy cows: a global overview

Among the challenges typically present in dairy livestock farming, heat stress in dairy cows emerges as a critical concern. The phenomenon, exacerbated by changing environmental conditions, underscores the necessity for innovative approaches to monitoring and management, particularly in regions where climatic impacts are most pronounced (S.L. Cartwright, 2023). Heat stress, a condition arising from the inability of animals to dissipate body heat effectively, has far-reaching implications for health, productivity, and welfare in dairy cattle. The phenomenon is particularly acute in Mediterranean regions of europe, including Spain and Italy, where rising temperatures and humidity levels, attributed to global climate change, exacerbate the challenges faced by livestock (Sabrina Hempel et al., 2019). The implications of these environmental shifts are profound, affecting not only the physiological well-being of dairy cows but also the economic sustainability of farms reliant on their productivity (S.L. Cartwright, 2023).

In response to these challenges, the role of sensor technologies in livestock management has become increasingly pivotal. Advancements in this domain offer a promising avenue for mitigating the impacts of heat stress through precise, real-time monitoring of animal health and environmental conditions. Wearable sensors, environmental monitoring systems, and data analytics platforms represent the forefront of this technological revolution, enabling farmers to make informed decisions that enhance animal welfare and farm efficiency. These tools provide actionable insights, facilitating the early detection of heat stress symptoms and the implementation of preventative measures, such as optimized cooling systems, altered feeding strategies, and modified housing conditions (W. Shu *et al.*, 2021).

By exploring the intersection of environmental challenges and technological solutions, this research underscores the significance of precision livestock farming in the modern era. The insights derived from this study aim to inform not only the academic community but also practitioners and policymakers, highlighting the potential of technology to revolutionize livestock management practices in the face of climate change.

## Chapter 2: Experimental study

This study marks a practical journey into the heart of dairy farming, where the well-being of cows is closely intertwined with farm productivity and the broader agricultural economy (Bjørn Gunnar Hansen, 2023). It is designed as a compass to navigate through the complex challenges of heat stress—a common yet formidable foe that can significantly impact animal health and farm profitability (D.Ramendra *et al.*, 2016). At the forefront of our exploration is a detailed collection of data, a critical step that forms the bedrock of our research. From the rhythms of daily cow behaviour to the subtle shifts in temperature and humidity, every piece of data collected is a puzzle piece essential to completing the bigger picture of farm life.

Transforming this data into a coherent narrative is where the analytical expertise truly comes into play. Through rigorous statistical analysis and the development of predictive models, we endeavour to comprehend, forecast, and manage the various factors that culminate in heat stress. The ultimate ambition is to equip dairy farmers with a decision-support tool, refined by data, that promotes timely and informed actions to protect the health of their cattle and optimize farm productivity through a personalized shower plan to use during summertime.

It is worth to highlight that the experimental part of this thesis is more than numbers and charts, It's about creating a future where dairy farms operate smoothly, where cows are healthier, and where farming is not just about making a living but about fostering a thriving, sustainable way of life. The hope is to contribute to make a step towards a smarter, kinder approach to farming—one that pays off for everyone, from farmer to cow to consumer.

## 2.1. Materials and Methods

The data for the study were collected from “MORE HOLSTEIN” Dairy cattle farm located in Bétera, the northermost region of Valencia city, Spain, where approximately 3.500 adult heads were breed. The original dataset included records collected from specific chosen groups of lactating cows (n = 65 ) from 26$^{th}$ of June 2022 to 30$^{th}$ of September 2022. Each record included the following informations:

- Animal collar ID, indicated as identification number of each on-neck accelerometers associated with each observed cow;
- Tested lactation group number, divided into two mid lactation groups (16, with additional shower session, and 17), fresh cows group (7), and end lactation/ drying cows group (20);
- Accelerometer data, containing all the behavioural records ordered by cow ID number (COLLAR), group number (GROUP NUMBER), and behaviours (Ingestion, Ruminatio,Panting) expressed as “minutes into behaviour”;
- Milk production data, containing the amount of produced by each observed cow. The milking data is divided into milk production recorded in each milking session (6:00, 14:00, 22:00) and the daily total milk production (Total);
- Meteorological dataset: a list of meteorological records of ambient temperature and humidity levels recorded by an on farm meteo-station. Data are expressed single hourly record of Temperature and Humidity levels;
- Cow feed consumption chart: data were retrieved by on an on farm weight scale and a digital scale associated with the unifeed mixer. The total daily consumption was calculated by subtracting the initial feed weight administered in each group and the trough residue. A second calculation has been deployed in order to an individual consumption chart for each observed group.
- Activity list: a list of hourly activity that identify the activity in which the animals were engaged.

Dairy cows were housed in free paddocks with a concrete floor, and sand-mix was used for bedding, which was renewed every weekdays. The animals were provided with 23 m2/head space and an 80 cm/head front manger. Cows were milked trice daily in herring-bone milking parlors equipped with an GEA FT® milk analysis system (GEA® Herd management). During summertime, cows have been showered for heat-stress mitigation. The frequency and time of shower were object of the research, so each observed group had a specific shower plan.

Milk production was recorded directly from the milking system and was available at the official milk recording date. The stage of lactation (SOL) was determined by considering a 30-day in milk (DIM) interval, defining the Post Partum group; from 91 to 150 for mid-lactation groups; from 151 to 210 for drying group. Parity was not considered for this specific research. There was no specific requisite for the minimum number of events recorded. In addition, milk yield and behaviour parameters did not undergo any pruning, in order to maintain records as real as possible for the predictive model creation. In conclusion, the final dataset used for statistical analysis and modelling consisted of 620616 records collected on the sampling days, covering cows.

## 2.2. THI calculation

At the time of retrieval, the meteorological dataset is missing a key component for the heat stress analysis in cow: THI Index, which is an index that measures environmental stress in animals and is based on temperature and humidity levels (Bohmanova, 2007). In particular:

Daily THI values were determined for the experimental period using the equation, THI Formula for Dairy Cows (Bohmanova, 2007):

$$\mathrm{THI} = (1.8 \times \mathrm{temperature}) - [(0.55 - 0.0055 \times \mathrm{humidity}) \times (1.8 \times \mathrm{temperature} - 26.8)] + 32$$

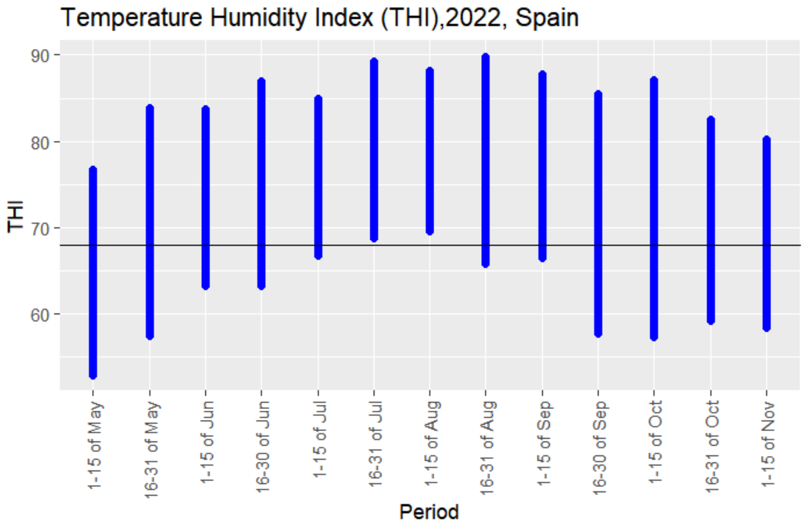


*Figure 1. THI Index progress in sampled observation period, 2022*

*Figure 1* provides a visual representation of THI over a series of months, showing 15-day periods measurements and their variability. It suggests a cyclical pattern in the data with elevated mean THI levels, which may be relevant for understanding environmental conditions affecting animal welfare.

The first chart presents the Temperature Humidity Index (THI) values across various periods in 2022 for Spain. THI is a critical indicator in dairy farming, as it combines temperature and humidity to gauge the risk of heat stress in cows. High THI values, generally above 68, suggest conditions that could lead to heat stress, which in turn can adversely affect cows' milk production, reproduction, and health. (Bohmanova, 2007) The chart shows that for much of the time, especially from June to September, the THI values are well above this threshold, indicating a high risk of heat stress during these warmer months, as highlighted by the horizontal line placed at 68 index point.

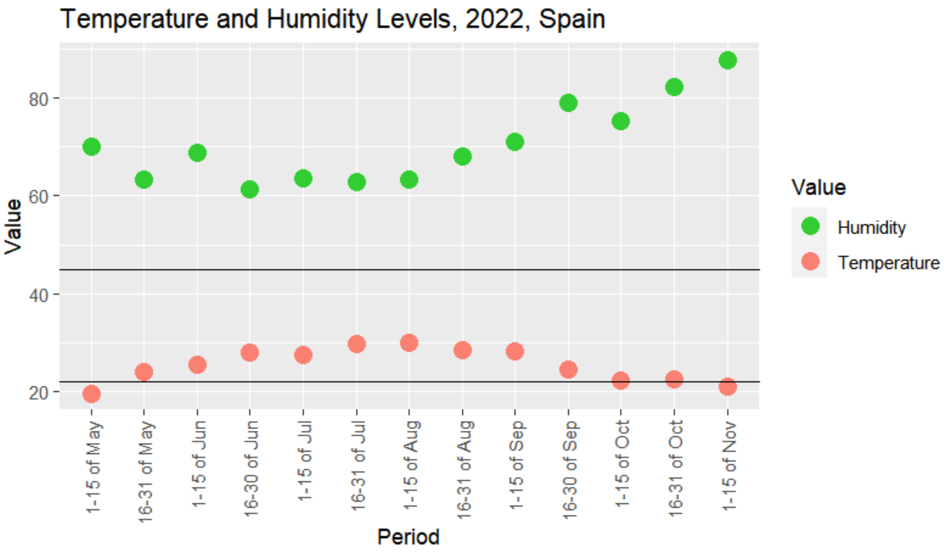


*Figure 2. Temperature and Humidity levels throughout the observation period, 2022*

*Figure 2* displays temperature and humidity independently for the same periods. Humidity values are consistently high, hovering above 60%, which is significant because higher humidity levels, above 45%, can intensify the effects of heat by reducing the ability of animals to cool themselves (W.Baldwin *et al.* 2023). The temperature remains relatively lower and stable, but when combined with high humidity, it creates a problematic environment for dairy cows as reflected in the THI values. However, temperature above 22° C can induce heat stress independently from its association with humidity levels (Bohmanova, 2007). The relevance of these charts in a dairy farming context is high. They underscore the periods when cows are at a greater risk for heat stress and thus inform management decisions.

## 2.3. Milk production.

The raw dataset contains all the productive data from each observed cow. Milk production is indicated within each cow for every day of production during the observation period, from 24/06/2022 to 22/09/2022. The different cow groups are classified as it follows:

- 16: Mid-Lactation group with shower time plan A;
- 17: Mid-Lactation group with added shower time plan B;
- 7: Postpartum group with added shower time;
- 20: Dry group with added shower time.

Every day of production is divided into 3 reference milking sessions: 06:00, 14:00, 22:00. The total daily production column is added to the dataset in order to help check the production progress of each cow. After a quick data analysis, the mean and total trends of milk production have been isolated.

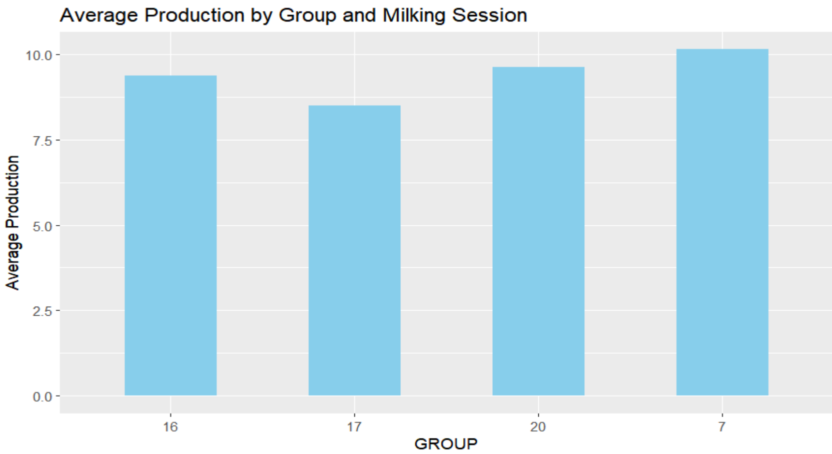


*Figure 3. Average milk production recorded daily for each milking session*

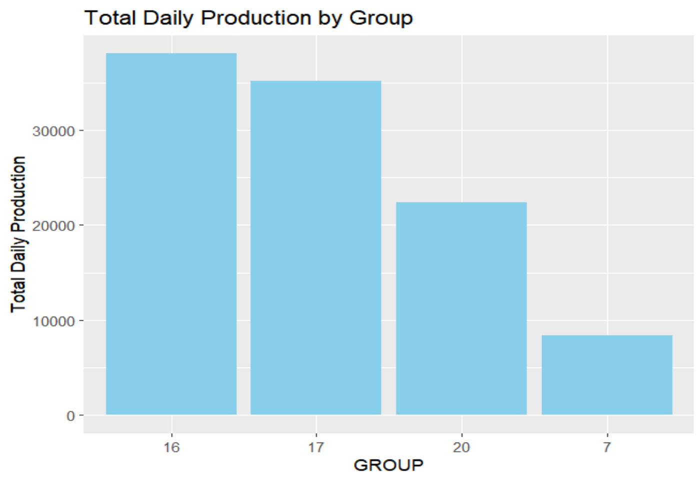


*Figure 4. Total milk production recorded daily from each group*

*Figure 3*, "Average Production by Group and Milking Session," shows the average milk production across various groups during milking sessions. The average production levels appear quite consistent across the groups, with only slight variations. None of the groups stands out as significantly higher or lower than the others due to a higher number of animals sampled for this specific study.

*Figure 4*, "Total Daily Production by Group," presents a starkly different picture. Here, we see the total volume of milk produced by each group over an entire day. The volumes change across the different groups due to the physiological stage of lactation of the different animals across the groups, with the mid lactation groups (16, 17) producing significantly higher quantities of milk as opposed to the dry group (20) and postpartum group (7).

## 2.4. Behaviour analysis

The current initial dataset contains individual accelerometer data of three main behaviours: **Ingestion**, **Rumination** and **Panting**. All the data are expressed as number of minutes spent in each activity for every hour of the day. The observation period goes from 20/06/2022 to 30/09/2022. A quick statistical analysis has underlined the following values:

| Ingestion | Rumination | Panting |
|---|---|---|
| Min. : 0.00 | Min. : 0.00 | Min. : 0.00 |
| 1st Qu.: 5.00 | 1st Qu.:22.00 | 1st Qu.: 2.00 |
| Median :11.00 | Median :33.00 | Median : 7.00 |
| Mean :14.88 | Mean :33.07 | Mean :13.38 |
| 3rd Qu.:21.00 | 3rd Qu.:43.00 | 3rd Qu.:18.00 |
| Max. :99.00 | Max. :98.00 | Max. :85.00 |

*Figure 5. Statistical and summaries of the three behaviours*

The summary statistics provided for Ingestion, Rumination, and Panting represent time spent on these activities measured in hours.

**Ingestion**

The statistics for Ingestion show that there is at least one cow (minimum value) that did not spend any time eating, which could indicate an issue, as cows typically eat for several hours a day. The first quartile at 5.00 suggests that 25% of cows spent less than 5 hours eating, which may be lower than expected for normal behavior, assuming a typical range of 3-5 hours of eating per day for high-producing dairy cows. The median value of 11.00 is more in line with normal behavior, though it suggests that half of the cows are eating less than the expected amount. A mean (average) of 14.88 could indicate that some cows are eating significantly more than others, skewing the average upwards, especially since the maximum value is 99.00, which is unusually high and could be an outlier or error.

**Rumination**

Rumination normally takes up about 30-40% of a cow's day. With a minimum of 0.00 and a first quartile at 22.00, it seems that at least 25% of cows are ruminating less than expected. The median of 33.00 and mean of 33.07 are both well within the typical range, indicating that at least half the cows are exhibiting normal rumination behavior. The max value at 98.00 is exceptionally high and not physiologically typical for rumination time, as it would leave almost no time for other essential behaviors.

**Panting**

Panting is a response to heat stress; cows typically pant less than they ruminate or eat. The provided statistics reflect this, with a median of 7.00, which would be expected on hotter days. A mean of 13.38 and a third quartile at 18.00 suggest that a significant number of cows are spending a considerable amount of time panting, possibly indicating a heat stress issue within the herd. The maximum value of 85.00 is extremely high for panting and is likely indicative of severe heat stress or a data recording error.

**Comparison with Normal Physiological Behaviour**

The median and mean values for rumination are consistent with normal cow behaviour, suggesting that the dataset includes many cows with typical rumination patterns. Ingestion and panting times show more variation, with the average (mean) higher than the median, indicating some cows are spending an unusually high amount of time on these behaviours. The max values for all three behaviours are unusually high and may represent outliers or errors in data collection.

**Additional descriptive analysis: Boxplot diagram**

A boxplot is a method for graphically showing the location, spread and skewness groups of numerical data through their quartiles.  The boxplot analysis of the three behaviours has been generated as it follows:

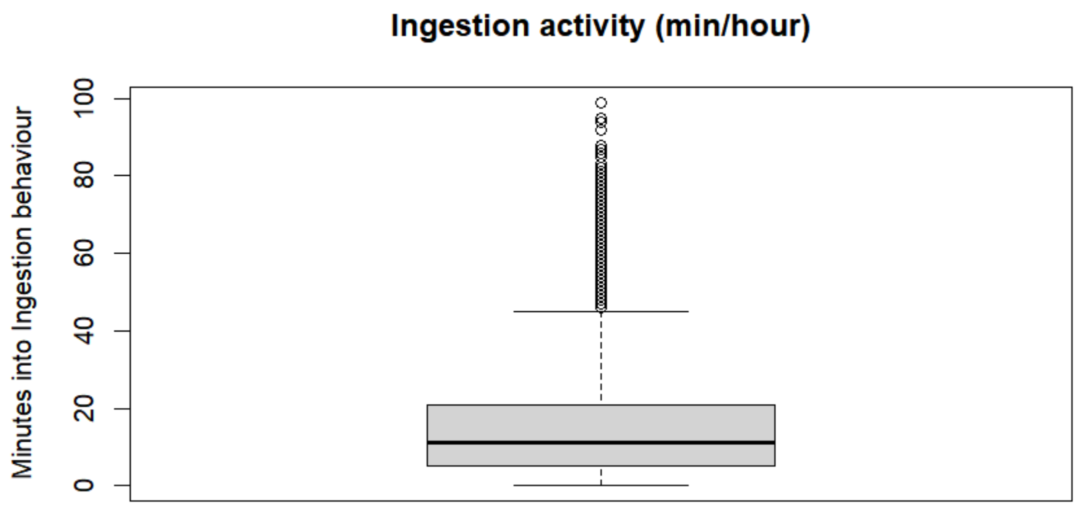


*Figure 6. A boxplot of the Ingestion behaviour*

The median value, indicated by the line within the box (*Figure 6*), is situated quite low on the scale. Altough it falls inside an optimal ingestion daily range (3 to 5 hours per day spent in  eating) this suggests that at least half of the cows are spending a relatively small portion of each hour engaged in eating, but a significant portion of animals are shown as not eating sufficiently. The interquartile range is narrow, showing that the middle 50% of cows have a relatively consistent ingestion behavior. However, the lower whisker extends quite close to zero, and the presence of a lower adjacent value suggests that there are cows with very low ingestion times. This could be due to various factors such as feed availability, health issues, or competition within the herd. There are several outliers showing that some cows have exceptionally high ingestion times. While higher ingestion times could be a sign of good appetite, such extreme outliers might also indicate stress, competition for food, or other behavioral issues. In summary, this boxplot suggests variability in ingestion behavior among the cows, with a number of them potentially not feeding as expected.

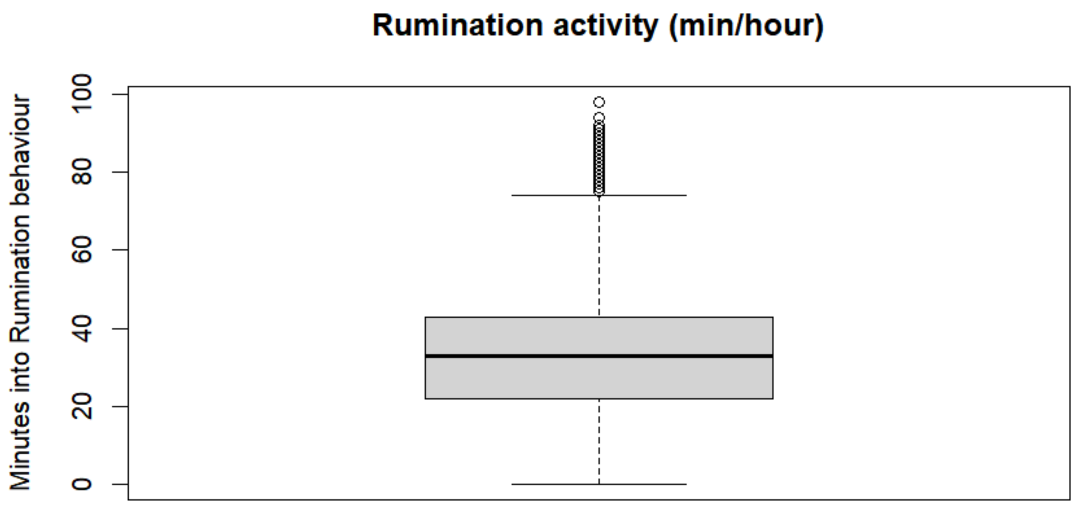


*Figure 7. A boxplot of the Rumination behaviour*

The boxplot of rumination activity (Figure 7) shows the majority of data  clustered within a middle range, with a median value that ideally falls within a range indicative of normal rumination behavior for dairy cows (18-24 minutes per hour). The median is centered and the box is symmetrical,  suggesting that half of the cows are ruminating within a consistent and potentially healthy range. The length of the whiskers would indicate a low variability of rumination behavior within the herd, and the presence of outliers above the upper whisker points to cows that are spending an unusually high amount of time ruminating, which might be due to factors such as diet, stress, or individual health issues. The median line near the middle of the box and the box not skewed significantly towards the top or bottom indicate that there is a physiological time into the behaviour for the majority of the herd. There are not may outliers, suggesting that may there be alterated data, as well as a small portion of animals ruminating for an unnatural long time, leading to a possible presence of abnormalities in the herd.

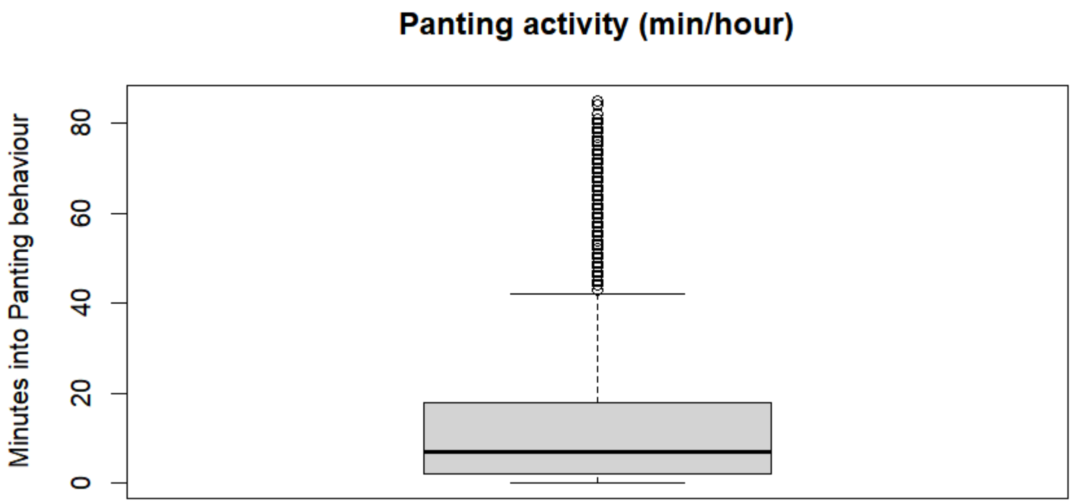


*Figure 8. A boxplot of the Panting behaviour*

The boxplot of panting activity (Figure 8) shows the majority of data clustered within a low range, with a median falling toward the lower end of the box, suggesting that more than half the cows have lower panting times on average. The IQR falls larger in the third quartile of the box, neat indication of a larger variability in panting times among the cows and larger time spent in panting for a greater portion of cows. The presence of many high-value outliers could indicate episodes of high temperature or humidity affecting the cows, prompting a necessary review of heat abatement strategies on the farm.

Delving into a specific behavioural analysis, it is possible to discover specific hourly trends of all the behaviours. This can be carried out, searching for descriptive patterns of the behaviours exploited in specific times of the day, as summarized in *Figure 9:* The provided times for the peaks of ingestion, rumination, and panting behaviours in dairy cows offer a snapshot into the daily patterns of these essential activities.

```
"Most Ingestion: 20:00:00:00"
"Least Ingestion: 06:00:00:00"
"Most Rumination: 05:00:00:00"
"Least Rumination: 20:00:00:00"
"Most Panting: 14:00:00:00"
"Least Panting: 01:00:00:00"
```

*Figure 9. Qualitative analysis of the most and least exploitation for each observed behaviour*

**Ingestion**

-Most Ingestion at 20:00: This peak suggests that cows are consuming the most feed in the evening. This could be due to cooler ambient temperatures making it more comfortable to eat for longer periods of time.

- Least Ingestion at 06:00: The lowest level of feeding activity occurring in the early morning might reflect a post-rumination rest period and the coincidence with the first milking session, psychologically preparing the cows for the start of a new daily cycle.

**Rumination**

-Most Rumination at 05:00: High rumination early in the morning indicates cows are likely processing feed consumed the previous day. This is expected as cows often ruminate more actively after periods of rest and when they are not actively feeding.

- Least Rumination at 20:00: The decrease in rumination during the evening hours coincides with the peak ingestion time, which is logical since cows will typically spend time eating rather than ruminating.

**Panting**

- Most Panting at 14:00: A midday peak in panting is consistent with the hottest part of the day, especially in the local climates with high temperatures that contribute to heat stress.

- Least Panting at 01:00: The least amount of panting at night aligns with lower temperatures and inactive periods when cows are less likely to be heat stressed.

The timing of these behaviours is significant for managing the health and productivity of the dairy herd. For instance, understanding that cows eat the most in the evening can influence decisions about feeding times and ration formulations to ensure optimal nutrient uptake and digestion.

The rumination peaks can inform the scheduling of quiet, restful periods that facilitate this crucial digestive process, with potential impacts on milk quality and quantity.

Knowledge of panting patterns drive heat abatement strategies, ensuring that cooling efforts are concentrated during the hottest parts of the day to alleviate the effects of heat stress.

## Chapter 3: Explorative Data Analysis

The study was structured in THREE parts: in the first part, the effect of THI index levels on MILK YIELD, BHEAVIOUR EXPLOITATION and MULTIVARIATE INFLUENCE was analysed, while in the second part, the aim was to try to clarify the effect of the current Shower plan on heat stress and its future modification for heat stress mitigation. The last part of this study is dedicated to Model Building and model testing for Shower plan personalization.

### 3.1. The effects of THI on milk production

The primary hypothesis of the study is that THI has a direct effect on milk production. This hypothesis posits that as THI rises, the physiological strain imposed on dairy cows escalates, resulting in diminished milk yields. Our statistical analysis aims to explore the magnitude and significance of this relationship, utilizing correlation matrices to elucidate how changes in THI correlate with variations in milk production volumes. Conversely, our null hypothesis maintains that THI has no effect on milk production. Under this scenario, any observed variations in milk yield would be attributed to other factors or random fluctuations, independent of THI levels.
The graphical representation of the relationship monitored by the milk production in the three milking sessions has been shown in *Figures 10, 11, and 12*:

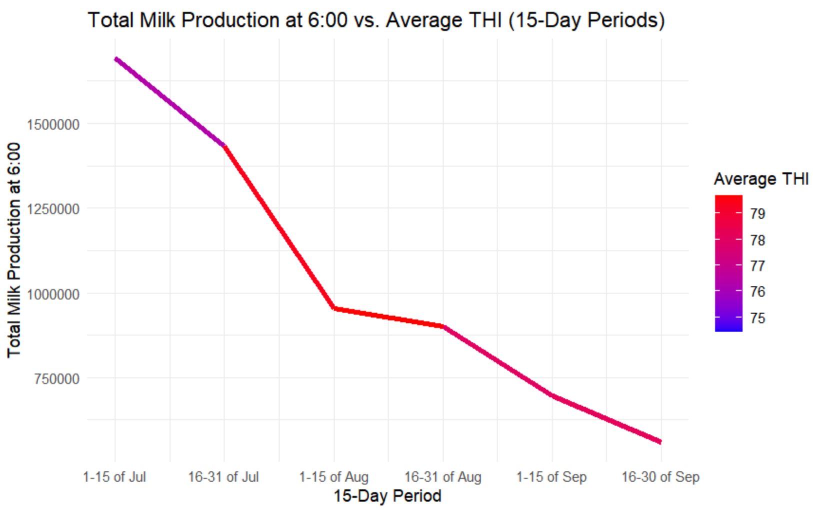


*Figure 10. Milk production trends under the influence of THI at 6:00*

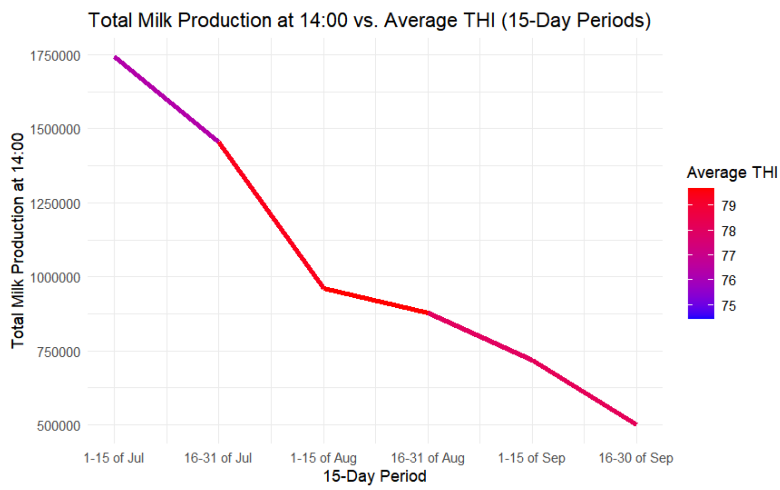


*Figure 11. Milk production trends under the influence of THI at 14:00*

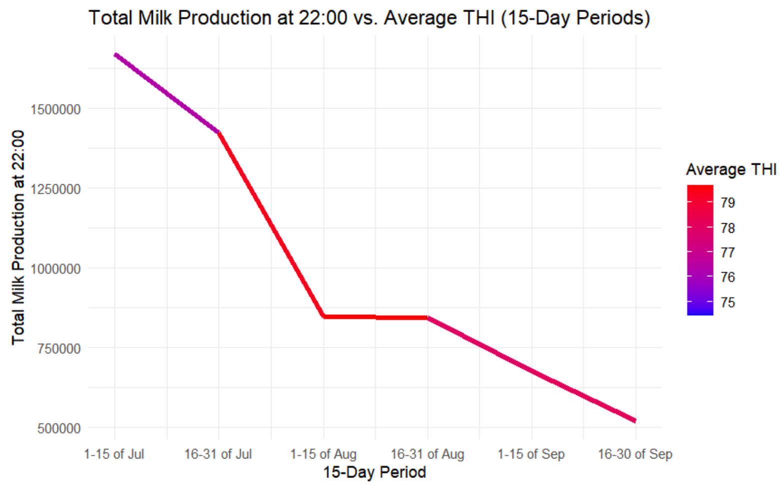


*Figure 12. Milk production trends under the influence of THI at 22:00*

In order to reject the null hypothesis and affirm the role of THI in influencing dairy cow productivity, or to conclude that THI is not a determinant factor within the context of our data set, we evaluate the statistical significance of the relationship between THI and milk production.
The relationship has been metaethically described expressing a simple linear relationship:

$$\boldsymbol{Y = \beta 0 + \beta 1 \times THI + \epsilon}$$

Where:

**Y** is the milk production.

**β0** is representing the expected milk production when THI is zero (theoretically, since THI cannot be zero).

**β1** is representing the expected change in milk production for each unit change in THI.

**THI** is the Temperature-Humidity Index.

ϵ is the error term, accounting for the variability in milk production that is not explained by THI.

This model assumes a linear decline in milk production with increasing THI, meaning for every unit increase in THI, milk production is expected to decrease by β1. The resulting correlation calculation between THI and total milk production has generated the following coefficient: **-0.1375.** The negative sign of the correlation coefficient indicates that as the THI increases, indicating higher levels of heat stress, the total milk production tends to decrease. This relationship is consistent with the understanding that heat stress negatively affects dairy cow productivity, impacting their ability to produce milk effectively. The strength of the correlation is light to moderate, with a value of -0.1375. This suggests a significant inverse relationship, meaning that changes in THI have a notable impact on milk production. Even if THI influences mil production, we cannot exclude also the presence of other factors affecting milk production.

In summary, the correlation coefficient of -0.1375 between milk production and average THI highlights the significant impact of heat stress on dairy cow milk production, emphasizing the need for effective heat stress management strategies in dairy farming. Testing the quality of the hypothesis strength leads to a direct assessment of the THI impact over the milk production observed in this dataset.

The testing has been carried on by a **Two-Sample T-Test or Welch test.**

**Welch Two Sample t-test:**

This test compares the means of two independent samples (THI and milk production, denoted as x and y). The t-value of -38.732 is again highly significant, with a p-value less than 2.2e-16, leading to the rejection of the null hypothesis that the true difference in means is equal to 0.

The negative t-value indicates that the mean of x (THI) is less than the mean of y (milk production). The 95% confidence interval for the difference in means ranges from -94599.14 to -85434.46, which doesn't cross zero, reinforcing that this difference is significant and not due to random chance.

The mean values for x (77.92276) and y (90094.72390) indicate that while THI values are high, suggesting stressful conditions for the cows, milk production figures are also very high. The Welch test is typically used when the variances of the two samples are assumed to be different, which might be the case here given the large difference in scale between THI and milk production figures.

**Interpretation:**

The significant difference in means between the average THI (THI_M) and total milk production (TOT_MILK), as shown by the Welch test, underscores the potential impact of THI on milk production. The negative t-value and the confidence interval suggest that as THI increases (indicating more heat stress), there might be a significant decrease in milk production, which aligns with the negative correlation previously discussed. Yet, the sample means provided show that despite high THI values, the average milk production is high. This could imply that the dataset includes periods or conditions where cows are still able to maintain high productivity, due to average effective heat stress mitigation strategies on the farm in question. Moreover, the results underscore the importance of considering environmental stressors in dairy farm management and the potential role of technological interventions to mitigate these impacts.

## 3.2. The effects of THI in Behaviour exploitation

Following the analysis on the dataset, the second goal of this EDA is to determine whether THI level have an impact on the behavioural exploitation of the observed cows (Ingestion, Rumination, Panting). The mathematical relationships between THI and the behaviors, assuming linear relationships, can be expressed as follows:

**Ingestion=** $\boldsymbol{\beta 0, Ing + \beta 1, Ing \times THI + \epsilon Ing}$

where:

**β0,Ing** is the x-intercept for ingestion, representing the baseline ingestion when THI is zero.

**β1,Ing** is the slope for ingestion, representing the change in ingestion behavior for each unit change in THI.

**ϵIng** is the error term for the ingestion model.

**Rumination=** $\boldsymbol{\beta 0, Rum + \beta 1, Rum \times THI + \epsilon Rum}$

where:

**β0,Rum** is the x-intercept for rumination**.**

**β1,Rum** is the slope for rumination**.**

**ϵRum** is the error term for the rumination model.

**Panting=** $\boldsymbol{\beta 0, Pant + \beta 1, Pant \times THI + \epsilon Pant}$

where:

**β0,Pant** is the x-intercept for panting.

**β1,Pant** is the slope for panting, which is expected to be positive as panting is a direct response to heat stress.

**ϵPant** is the error term for the panting model**.**

The correlation matrix is graphically represented in *Figure 13*:

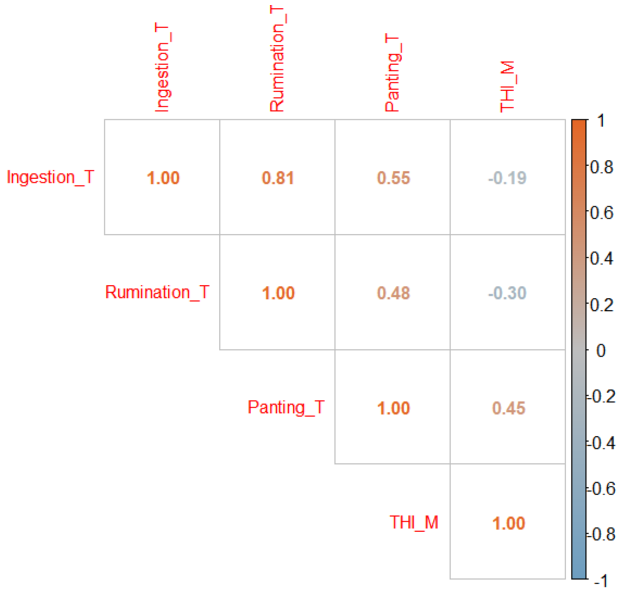


*Figure 13. Correlation heatmap of behaviours relationships' under the infulence of THI*

- **Total Ingestion and Rumination time** (**Ingestion_T and Rumination_T) (0.81)**: This strong positive correlation indicates that as ingestion time increases, rumination time also increases. This relationship is expected as more feed intake generally requires more rumination time for proper digestion.

- **Total Ingestion and Panting time** (**Ingestion_T and Panting_T) (0.55)**: A moderate positive correlation suggests that as ingestion time increases, panting time also tends to increase. This could indicate that cows that eat more may also be more prone to heat stress, or it could reflect that cows are more active (and thus pant more) during times when they are also eating more.

- **Total Ingestion time and Average THI (Ingestion_T and THI_M) (-0.19**): A weak negative correlation means that higher THI values are slightly associated with lower ingestion times. This is consistent with the understanding that heat stress can reduce feed intake in cows.

- **Total Rumination and Panting time (Rumination_T and Panting_T) (0.48):** A moderate positive correlation indicates that cows with higher rumination times also tend to have higher panting times. Since rumination is a heat-producing process, it's plausible that cows might pant more as rumination increases.

- **Total Rumination time and Average THI** (**Rumination_T and THI_M) (-0.30):** This negative correlation suggests that as the THI increases, indicating hotter conditions, cows spend less time ruminating. This makes sense because heat stress can disrupt normal rumination behavior.

- **Total Panting time and average THI (Panting_T and THI_M( (0.45):** A moderate positive correlation is observed here, which indicates that as THI increases, panting time also increases.

This is to be expected as THI is an indicator of heat stress, and panting is a cooling mechanism in cows. The negative correlations between THI and both ingestion and rumination times suggest that higher temperatures and humidity levels, may disrupt normal feeding behaviors and could potentially lead to lower milk production, as well as overall cow health. Meanwhile, the positive correlation between panting time and THI emphasizes the need for effective heat stress management strategies, especially in hot climates or during summer months.

## 3.3. Multivariate Analysis

Since the relationship between Panting behaviour and THI has not shown a strong correlation score, this could denote the presence of multifactorial causes that can decrease the effectiveness of the relationship itself.

The last step of this exploratory data analysis would investigate the interrelation between milk production, behaviours (Ingestion, Rumination, Panting), and environmental factors (THI, Temperature, Humidity, Feed Consumption).

$$\boldsymbol{MilkProduction} = \boldsymbol{\beta 0} + \boldsymbol{\beta 1} \times \boldsymbol{Ingestion} + \boldsymbol{\beta 2} \times \boldsymbol{FeedConsumption} + \boldsymbol{\beta 3} \times \boldsymbol{Rumination} + \boldsymbol{\beta 4} \times \boldsymbol{THI} + \boldsymbol{\beta 5} \times \boldsymbol{Temperature} + \boldsymbol{\beta 6} \times \boldsymbol{Humidity} + \boldsymbol{\beta 7} \times \boldsymbol{Panting} + \boldsymbol{\epsilon}$$

Which:

**Milk Production:** The dependent variable subject of the correlations.

**β0**: The intercept, representing the expected value of milk production when all other variables are zero.

**β1 to β7β7:** The coefficients for each independent variable, which measure the expected change in milk production for a one-unit change in that variable, holding all other variables constant.

**Ingestion, Feed Consumption, Rumination**: The dependent variables that are thought to be affected by the independent variables and in turn affect milk production.

**THI, Temperature, Humidity, Panting**: The independent variables that are expected to influence both the dependent variables and milk production directly.

**ϵ**: The error term, representing unobserved factors that affect milk production.

The graphical resolution of the correlation matrix shows as in *Figure 14*:

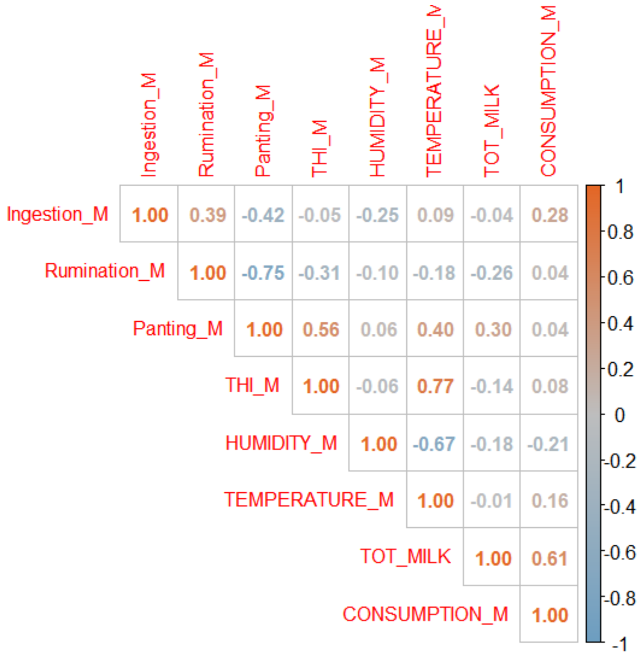


*Figure 14. Multivariate correlation matrix.*

**Ingestion and Rumination (0.39):** A moderate positive correlation indicates that as cows spend more time eating, they also spend more time ruminating. This relationship is expected as increased feed intake typically requires more rumination for digestion.

**Ingestion and Panting (-0.42)**: A moderate negative correlation suggests that as ingestion increases, panting decreases, which may indicate that cows eat less when they are under heat stress.

**Rumination and Panting (-0.75)**: A strong negative correlation; as cows spend more time ruminating, they spend significantly less time panting. This might be explained by the fact that rumination typically occurs during cooler periods of rest, while panting is associated with heat stress. Added confirmation comes with the moderate negative correlation between rumination and THI (**-0.31**), stating less rumination with increased heat stress conditions.

**Panting and THI (0.56)**: A strong positive correlation reflects that panting increases with higher THI values, confirming that panting is a behavioral response to heat stress, evenly positively correlated with temperature (**0.40**).

**THI and Temperature (0.77)**: A strong positive correlation, indicating that as temperature increases, the THI also increases, which is consistent since THI is a function of both temperature and humidity.

**Milk Production and Feed Consumption (0.61)**: A strong positive correlation indicates that higher feed consumption is associated with higher milk production, which is a well-documented relationship in dairy farming.

The significance of this data lies in its ability to guide farm management practices. The relationships between cow behavior, environmental factors, and milk production can help optimize conditions for animal welfare and productivity. The strong negative relationship between humidity and milk production may prompt the better use of cooling systems during humid periods to maintain milk output. The correlations involving panting and THI could also support the implementation of heat stress mitigation strategies to ensure cow comfort and sustained milk production at its best.

# Chapter 4: Shower Plan Programming

Starting from the insightful correlations illustrated in previous sections, the second part of the experimental chapter aims to design and validate a data-driven shower plan for dairy cows. The imperative for such an intervention crystallizes from the observed inverse relationships between heat stress indicators, such as THI, and crucial aspects of dairy cow productivity and welfare, notably rumination time and milk yield. The correlation heatmap in *Figure 14* laid a compelling foundation, revealing that as THI escalates, the vital behaviours of rumination, ingestion, and milk production exhibit a marked decline. This trend underscores the impact of heat stress on dairy cow physiology, echoing the need for proactive management strategies.

Given the delicate interplay between environmental conditions and animal well-being delineated by our analysis, this chapter endeavours to harness the predictive power of the amassed data. Exploiting the positive correlations between ingestion time and milk production, we aim to update a bespoke showering regimen that mitigates the discomfort inflicted by heat stress. The premise of this regimen is to synchronize cooling interventions, namely showering, with the cows' natural behavioural rhythms and the diurnal fluctuations of THI, to optimize welfare and productivity.

This experimental chapter is not merely an exploration of empirical data but an ambitious stride towards a tangible application that could revolutionize the paradigm of dairy farm management under the spectre of global climate change. It aims to calibrate shower timing, duration, and frequency to the thermal thresholds signified by our findings, thus offering a tailored solution to the heat stress conundrum.

## 4.1. Descriptive Statistics

A preliminar qualitative analysis is useful to inspect whether the current shower plans have any effect on the analysed herd groups. The first important aspect to determine would be the research of any positive effects of showers over the panting behaviour. *Figure 15* graphically compares panting scores between showered cows (right boxplot) and not showered cows (left boxplot).

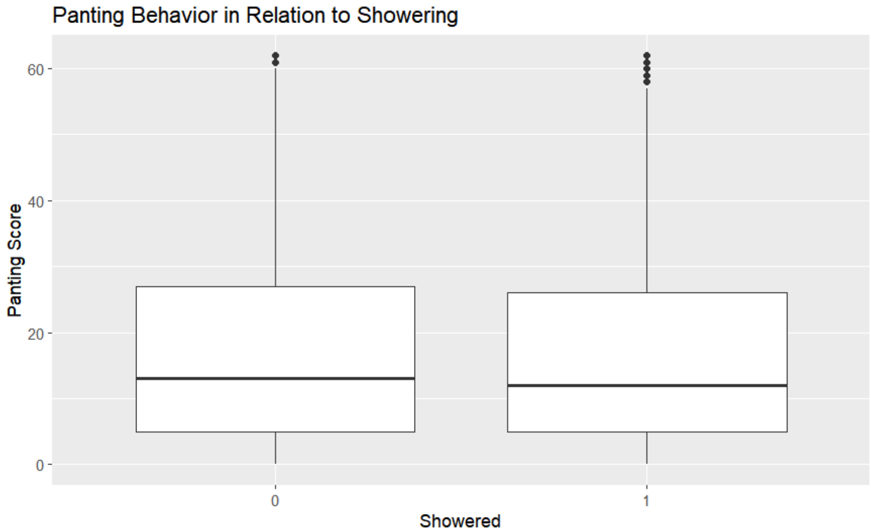


*Figure 15. A Boxplot  showing the effect of the shower plan in showered (1) cows as opposed to not showered (0) ones.*

**Median**: The median panting score is approximately the same for both showered and not showered groups, suggesting that showering does not have a clear effect on the median level of panting behavior.

**Spread of Data**: The interquartile range is slightly tighter for the showered cows, which could indicate that showering may lead to a more consistent (homogenous) response in panting behavior across the group. However, the difference is not pronounced.

**Outliers**: There are outliers in both groups, more extreme for  the showered cows, indicating episodes of very high panting scores.

**Range**: Both groups show a wide range of panting scores, but the range is slightly more compressed for the showered cows, indicating that showering might reduce the variability in panting behavior to some extent.

While summarizing the two boxplots indicates that showering does not significantly alter the median panting behavior, the reduced spread and range in the showered group could imply a moderate effect of showering on the consistency of panting behavior across that group. Additionally, the presence of outliers, especially in the showered group, suggests that both shower factors and others than showering might influence panting scores, and these would need to be investigated to understand the full impact of showering on heat stress management.

The second aspect to analyse would be to determine if the current shower plan has any effect over milk production due to heat tress mitigation. *Figures 16 to 18* graphically compare milk production performance between showered cows (right boxplot) and not showered cows (left boxplot) throughout the three milking sessions.

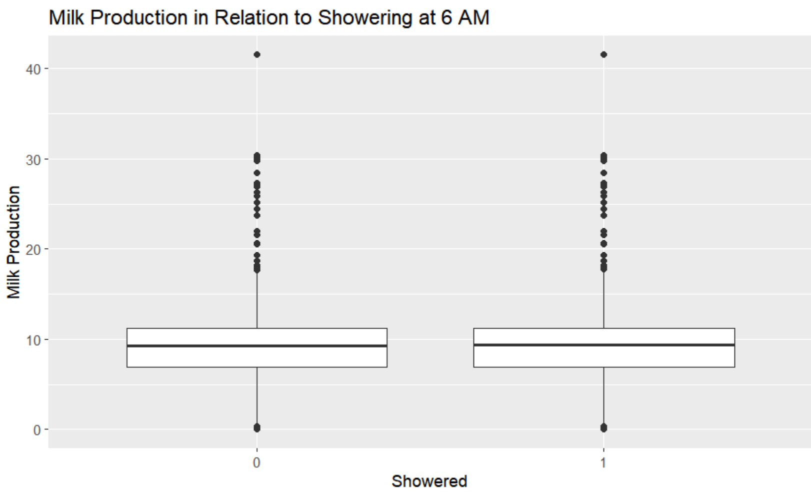


*Figure 16. Milk production under the influence of the shower plan in 6 am milking session*

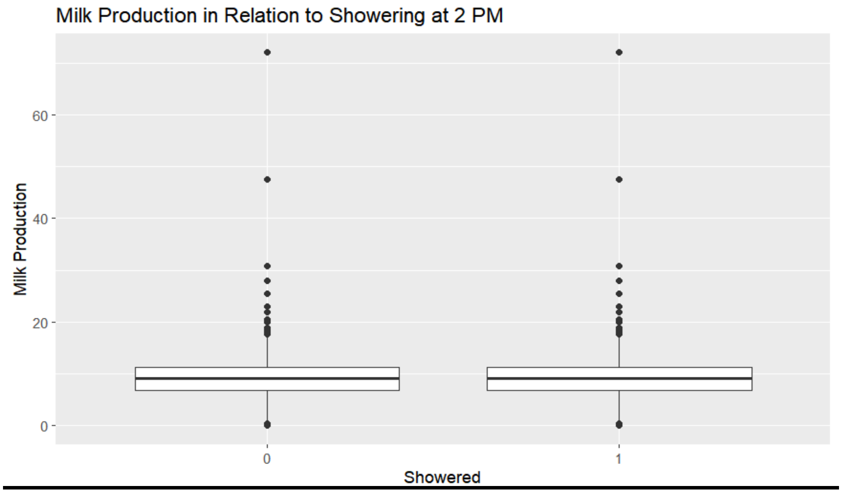


*Figure 17.. Milk production under the influence of the shower plan in 2 pm milking session*

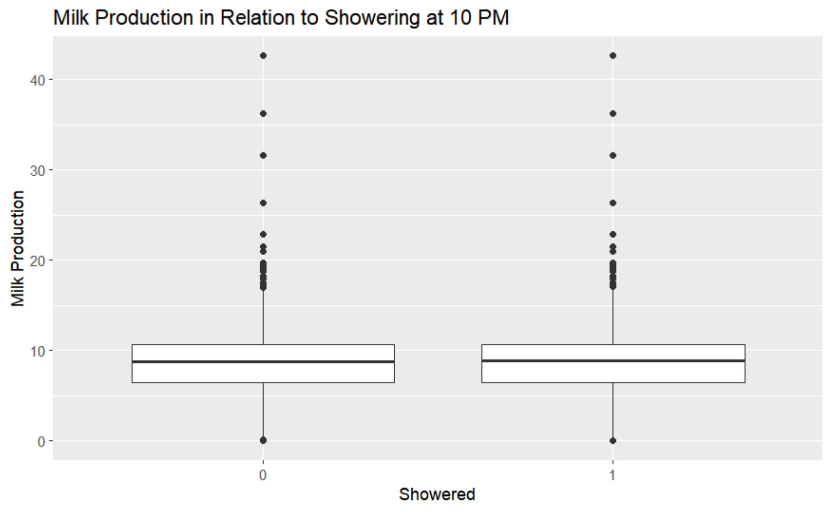


*Figure 18. Milk production under the influence of the shower plan in 10 pm milking session*

**Median Milk Production**: The median milk production appears very similar for both showered and non-showered cows, indicating that showering does not have a strong median effect on milk production.

**Interquartile Range (IQR)**: The IQR, which indicates the middle 50% of the data, is comparable for both groups. This suggests that showering right before milking and randomly during the hottest hours of the day has not markedly changed the central tendency of milk production in the observed cows.

**Range of Milk Production**: The range is similar for both groups, indicating that showering does not significantly change the overall variability in milk production.

**Outliers**: Both the showered and non-showered groups display outliers, with individual data points scattered above the upper whisker. The presence of outliers in both groups suggests that there are cows with milk production that is notably different from the main group.

Based on the boxplot, it can be inferred that the act of showering cows does not have a substantial impact on the central tendency of milk production. However, it's important to consider other factors that could influence milk yield, such as the cows' overall health, nutritional status, and the ambient conditions of the days measured. The similar distribution of milk production across showered and non-showered groups might suggest that other management practices or environmental factors are at play, which may be equally or more influential on milk production than the showering routine at the specified time.

## 4.2. Model building.

Interaction models provide insights into how various factors combine to influence outcomes like panting behaviour and milk production. The relationship between milk production, panting times and environmental conditions is already neatly affirmed. Therefore, creating a direct relationship between all beahviours, environmental conditions, and milk production can help direct the effects of management practices on cow wellness and heat stress alleviation. All that being said, creating a personalised shower plan requires to consider all the influential variables affecting and enhancing heat stress response in dairy cows. For its ease of use and computational reliability, the chosen model structure in this research is the linear regression model.

Considering panting behaviour as the most suitable predictor for heat stress, we are building the predicting model based on the following relationship:

$$\boldsymbol{Panting = \beta 0 + \beta Sh + \beta thi + \beta t^{\circ} + \beta c + \beta r + \beta i + \beta shf + \epsilon}$$

Where:

**Panting**= is the dependent variable, expressed in minutes.

**β0** = the intercept term, representing the average value of panting when all predictor variables are 0.

**Bx =** the coefficients for each predictor variable, representing the average change in Panting for one unit of change in the predictor variable, holding all other predictors constant (Shower, THI, Temperature, Consumption, Rumination, Ingestion, Shower Frequency respectively)

**ϵ** = is the error term, accounting for the variation in panting not explained by the model.

The performance results of the predictive model are indicated in the table in *Figure 19.*

| Residual standard error | 10.81 on 310299 degrees of freedom |
|---|---|
| Multiple R-squared | 0.5542 |
| Adjusted R-squared | 0.5542 |
| Model accuracy | 55,42% |
| F-statistic | 4.822e+04 on 8 and 310299 DF |
| p-value | <0,001 |

*Figure 19. Model Performance evaluation parameters.*

**Model Fit**

**Residual Standard Error (RSE)**: Approximately 10.81, which gives the average amount that the response will deviate from the true regression line.

**Multiple R-squared: 0.5542** indicates that around **55.42%** of the variability in Panting is explained by the model. This is a moderate amount, showing that the model has a decent fit.

**Adjusted R-squared**: very close to the R-squared value, suggesting that the number of predictors in the model is appropriate for the size of the data.

**Mean Absolute Error** = **8.783261**. The MAE is lower than RMSE since there are errors in prediction for extreme values (squared in RMSE, thus amplifying the error). A MAE of approximately 8.78 indicates that, on average, predictions are within about 8.78 units of the actual values. MAE provides a more intuitive measure of average error.

**F-statistic**: The F-statistic and its associated p-value (< 0.001) suggest that the model as a whole is statistically significant. This means that there is a relationship between the predictors and the dependent variable that is highly unlikely to have occurred by chance. The $R^2$ score suggests that the model is moderately effective, explaining over half of the variance in dependent variable with the predictors used. The RMSE and MAE values give an idea of the average magnitude of the model's errors. While not trivial, these errors should be contextualized against the range and distribution of panting scores. If panting varies greatly (say, from 0 to 100), an RMSE of around 10 might be considered more acceptable than if panting scores ranged closer together. The predictors performance is stated in the table from *Figure 20.*

| Regression parameter | Intercept | Showered | THI | TEMPERATURE | HUMIDITY | CONSUMPTION | RUMINATION | INGESTION | SHOWER FREQUENCY |
|---|---|---|---|---|---|---|---|---|---|
| Estimate | -3,78E+04 | -2,91E+02 | -3,14E+02 | 2,83E+03 | 3,13E+02 | 2,02E+02 | -5,50E+02 | -7,29E+02 | 5,68E-01 |
| Std. Error | 7,42E+02 | 4,51E+01 | 2,30E+01 | 3,30E+01 | 3,56E+00 | 6,88E+00 | 1,57E+00 | 2,46E+00 | 9,72E-02 |
| t value | -50.927 | -6.451 | 2,30E+01 | 85.840 | 88.097 | 29.378 | -350.355 | -296.538 | 5.846 |
| Pr(>\|t\|) | < 2e-16 *** | 1.11e-10 *** | < 2e-16 *** | < 2e-16 *** | < 2e-16 *** | < 2e-16 *** | < 2e-16 *** | < 2e-16 *** | < 2e-16 *** |
| | | | | *** | p-value < 0,001 | | | | |

*Figure 20. Model Predictors performance over the predicted Panting variable.*

## Coefficients

(**Intercept**): The model intercept is **-37.78** with a highly significant p-value, suggesting the intercept is significantly different from 0.

**Predictors**: All predictors are statistically significant, as indicated by the p-values (< 2e-16 for most, with Shower Frequency at 5.04e-09), meaning they contribute meaningfully to the model. The signs of the coefficients indicate the direction of their relationship with the dependent variable (Panting):

**showered**, **THI**, and **ingestion** have negative coefficients, indicating that increases in these predictors are associated with a decrease in Panting scores.

**temperature**, **humidity**, **consumption**, and **rumination** have positive coefficients, suggesting that increases in these variables are associated with an increase in Panting scores.

**SHOWER FREQUENCY**: A very small positive coefficient suggests a slight increase in Panting scores with more frequent showering, which might seem counterintuitive and warrants further investigation.
The computed model denotes a statistically significant relationship between the set of predictors and the panting score, explaining over half of the variability in the panting scores. Given the signs and significance of the coefficients, each predictor plays a clear role in the model.

# Chapter 5: Results

Through a comprehensive data analysis process, we developed a strategic showering frequency program aimed at mitigating heat stress in dairy cows. The evaluation function incorporated a baseline for Thermal Heat Index (THI) wellness, taking into account critical environmental parameters: a THI above 68, temperatures exceeding 22 degrees Celsius, or humidity levels over 45% (Bohmanova, 2007). These thresholds were determined based on their significant impact on cow comfort and milk production efficiency.
The prediction algorithm, trained on a subset of historical data, was rigorously tested and validated against a separate set of data to ensure accuracy and reliability. Let f represent the frequency per day at which a certain action (e.g., showering cows) is taken, with $f \in \{1,2,3,4,5\}$.

For each frequency (*f)*, we simulate a score (s) such that $s \sim Uniform(5,10)$

We have a target panting score (*ptarget* ) and we're trying to find the frequency (*fopt) that* minimizes the absolute difference between the simulated score ss and the target score (*ptarget*,) which can be expressed as:

$$\boldsymbol{fopt = argminf \mid sf - ptarget \mid}$$

Where:
***sf*** is the simulated score for frequency *f.*
***ptarget*** is the target panting score we aim to achieve.

The algorithm iterates through a set range of frequencies and keeps track of the best score and the associated frequency by updating the current best score (*sbest)* and optimal frequency (*f*opt) if the new score is closer to the target score than the previous best.

The mathematical representation of the update rule when a better score is found can be stated as:

$\boldsymbol{If\ \mid s - ptarget \mid < \mid sbest - ptarget \mid, then\ set\ \{sbest = s\ \{fopt = f}$

At the end of the simulation, fopt and sbest represent the optimal showering frequency per day and the achieved average panting score, respectively. If no optimal solution is found within the simulated range, the algorithm reports that no solution was found.

The prediction algorithm, trained on a subset of historical data, was rigorously tested and validated against a separate set of data to ensure accuracy and reliability. The result of this meticulous process is a refined shower plan tailored to optimize cow welfare. Initially, the **mean panting score** observed in the herd was at **17.44**, well above the comfort zone. Our **target** was a **panting score** of **7**, which aligns with established standards for adequate animal welfare and heat stress management (N. Morgado *et al.* 2023).

The Strategy Impact Reduction has been analysed as it follows:

$$\boldsymbol{Reduction\ Percentage = \left(\frac{Initial\ Mean\ Panting\ Score - Achieved\ Average\ Panting}{Initial\ Mean\ Panting\ score - Target\ Panting\ Score}\right) 100}$$

The resulting Reduction Percentage stands at **≈90.42%**

After applying our model, the suggested optimal shower frequency was set at four times per day, as shown in F*igure 21*.

| Model Generated Value | min/hour |
|---|---|
| Mean panting score | 17.44 |
| Target panting score | 7 |
| Optimal shower frequency per day | 4 |
| Achieved average panting score | 8 |

*Figure 21. Algorithm-Generated Shower Frequency Program*

This regimen aimed to significantly reduce the panting score and thus alleviate the signs of heat stress. Upon implementing this optimized showering schedule, we have successfully **reduced the mean panting score to 8**. While this figure narrowly misses our target, it represents a substantial improvement from the initial observations. The slight deviation from our target panting score suggests that further refinements to the shower plan may be required, possibly incorporating additional environmental control measures, or adjusting the timing of showers to align more closely with the hottest periods of the day.

Our data-driven approach testify the potential of predictive modelling in enhancing livestock management practices. With ongoing adjustments and continuous monitoring, we are confident that the welfare of the dairy cows can be significantly improved, leading to better health outcomes and sustained productivity.

# 5.1. Discussion

Heat stress in dairy cows has emerged as one of the most pressing issues in dairy farming, significantly impacting animal comfort, welfare, and productivity (University of Minnesota, 2023). As global temperatures continue to rise, the frequency and severity of heat stress events are increasing, making it a critical concern for the dairy industry (Thornton P. *et al.* 2022). Heat stress not only compromises the well-being of dairy cows but also affects the efficiency of milk production, leading to substantial economic losses for farmers (J. Liu *et al* 2019).

The core of the problem lies in the cow's ability to dissipate body heat. Unlike humans, cows have a limited capacity to sweat, making it challenging for them to cool down effectively during hot and humid conditions (G.Gujad *et al.* 2023). This inability to maintain a normal body temperature under heat stress conditions can lead to a range of adverse effects, including decreased feed intake, altered metabolic rates, and reduced fertility, all of which directly influence milk yield and quality (G.Gujad et al. 2023).

To monitor and manage heat stress in dairy cows, dairy farmers and researchers rely on several key indicators. The Temperature-Humidity Index is one of the most widely used metrics to assess heat stress risk. THI takes into account both ambient temperature and relative humidity to provide a comprehensive measure of the environmental conditions that contribute to heat stress (G. Hoffman *et al.* 2020). By monitoring THI levels, farmers can implement timely interventions to mitigate the impact of heat stress on their herds.

In addition to environmental metrics like THI, observing basic cow behaviors such as ingestion (eating), rumination (cud chewing), and panting provides valuable insights into the animals' heat stress levels (Frigeri *et al,* 2022). Under normal conditions, dairy cows spend a significant portion of their day engaging in feeding and rumination activities. However, as heat stress intensifies, there is a noticeable shift in these behaviors. Affected cows tend to reduce their feed intake, leading to lower energy consumption and, consequently, decreased milk production. Rumination, a critical process for digestion and nutrient absorption, also declines, further compromising the cows' nutritional status (Frigeri et al, 2022). Meanwhile, increased panting serves as a physiological response to dissipate excess body heat, yet it signifies that the cow is experiencing discomfort.

The direct influence of heat stress on these basic behaviors underscores the interconnectedness between animal welfare and productivity. Reduced ingestion and rumination not only indicate compromised welfare but also directly lead to lower milk yields. Therefore, managing heat stress through environmental modifications (e.g., shade, ventilation, and cooling systems) and nutritional adjustments is crucial to maintaining herd health, welfare, and productivity.

In summary, the challenge of heat stress in dairy cows highlights the need for comprehensive monitoring strategies, encompassing both environmental conditions and animal behaviors. By understanding the multifaceted impacts of heat stress, dairy farmers can implement effective mitigation strategies, ultimately enhancing the well-being of their cows and the sustainability of milk production.

Building on the recognition that heat stress in dairy cows presents a significant challenge to animal welfare and milk production efficiency, this study aims to explore and refine the use of shower cooling systems as a viable solution for alleviating heat stress. The objective is to shift towards data-driven management practices that can dynamically respond to the varying needs of the herd under different environmental conditions. By harnessing detailed animal behavior databases, this research seeks to develop a personalized shower plan that not only addresses the immediate discomfort caused by heat stress but also contributes to a more sustainable and efficient heat stress mitigation system.

The cornerstone of this approach lies in the integration of real-time data analytics with traditional heat stress management practices. By analyzing patterns in ingestion, rumination, panting, and milk production in relation to THI levels, we aim to unveil nuanced insights into how different cows respond to heat stress. This information serves as the foundation for a targeted cooling strategy, leveraging shower systems to provide relief when and where it is most needed. Unlike one-size-fits-all solutions, a personalized shower plan promises to optimize resource use, minimize stress for the animals, and maintain or even improve milk production during hot weather periods.

Thus, this study not only contributes to the existing body of knowledge on effective heat stress alleviation practices but also introduces a novel application of data-driven decision-making in dairy farm management. Through careful analysis and the development of custom shower schedules, we endeavor to demonstrate the potential of technology and data analytics to enhance animal welfare and operational efficiency in the face of climate challenges. The findings of this study reveal significant insights into the impact of heat stress on dairy cow behavior and milk production in the observed heard, underpinned by a high critical weather exposure percentage of 97.81%. This pervasive exposure to adverse weather conditions underscores the urgent need for effective heat stress mitigation strategies in dairy farming.

Our analysis identified a relatively low percentage of observations with abnormal rumination at 1.35%, suggesting that while most cows maintain their rumination activity, a small fraction experiences recurrent disruption in this crucial behavior. In contrast, abnormal ingestion and panting were observed at considerably higher rates, 26.29% and 59.10%, respectively. These findings indicate that heat stress has a more pronounced effect on feeding behavior and respiratory distress, with over half of the observed cows displaying signs of heat-induced panting, a clear indicator of discomfort and heat stress.

The direct impact of heat stress on milk production was quantified through the analysis of milk loss across different THI ranges. The results demonstrate a progressive increase in milk loss with rising THI levels, signaling the detrimental effects of heat stress on lactation performance. Specifically, the study documented milk losses of 184 units for the THI range of 68-72, escalating to 184 units for THI 73-77, and reaching 184 units for the THI range of 78-82. These findings highlight the critical relationship between THI and milk production, with higher THI levels corresponding to increased milk loss, thereby affirming the necessity for targeted interventions to combat heat stress.

In summary, the pervasive exposure to critical weather conditions, combined with the observed impacts on rumination, ingestion, and panting behaviors, as well as the significant milk production losses, underscores the pressing challenge posed by heat stress to dairy cow welfare and farm productivity. The data-driven analysis conducted in this study lays a foundation for the development of personalized shower plans as a viable solution for mitigating heat stress, offering a promising avenue for enhancing animal welfare and ensuring sustainable milk production in the face of escalating climate challenges. In addressing the multifaceted challenge of heat stress in dairy cows, our study harnessed the power of linear modelling to dissect the intricate dynamics between various environmental and physiological variables and their collective impact on panting behavior—an unequivocal indicator of heat stress. Through a comprehensive analysis that spanned temperature-humidity index (THI), temperature, humidity, and critical cow behaviors such as rumination and ingestion, the linear model emerged as a pivotal tool in decoding the subtleties of heat stress manifestation in dairy herds.

Central to our findings was the model's ability not only to elucidate the direct and interactive effects of these variables on panting but also to leverage this insight in crafting a data-driven intervention strategy. The simulation of the shower cooling system, informed by the linear model's predictions, underscored the potential of precision livestock farming techniques in mitigating heat stress. The implementation of the simulated shower plan on test data yielded a mean panting score of 17.44, a figure reflective of the initial stress conditions. The subsequent optimization of the shower plan, predicated on the model's insights, set forth an optimal shower frequency of four times per day. This targeted intervention heralded a significant downturn in the achieved average panting score, plummeting to 8.00—an approximation to the physiological norm and signifying an impressive reduction in heat stress manifestation by approximately 90.42%. Such a pronounced decrease not only attests the efficacy of the shower plan but also to the model's capacity in guiding precision interventions that yield substantial improvements in animal welfare.

The linear model developed for analyzing panting behavior under various environmental and physiological variables holds profound implications for modern dairy management practices. Its utility extends far beyond the academic exploration of heat stress impacts, positioning itself as a highly practical tool for incorporation into today's dairy farm management systems. The model's predictive capability, underpinned by rigorous data analysis, offers a bridge to more personalized, efficient, and responsive dairy herd management strategies, especially in the context of mitigating heat stress.

The potential for integrating this predictive algorithm into current farm management software and sensor technologies is particularly promising. Modern dairy operations are increasingly reliant on digital tools and IoT (Internet of Things) solutions for monitoring animal health, behavior, and productivity. By embedding our linear model into these systems, farmers could achieve real-time monitoring and predictive insights into heat stress conditions, enabling preemptive actions to safeguard animal welfare and optimize production. Such integration would enhance existing meta-analyses of factors affecting milk production by incorporating a nuanced understanding of how heat-induced metabolic energy loss and altered panting behavior directly impact lactation. This enriched data layer would not only facilitate more informed decision-making but also refine the algorithms that today's dairy management platforms use to predict and react to various stressors. Moreover, the model's application could revolutionize the design and implementation of environmental control systems within barns, such as automated cooling and ventilation systems. By predicting periods of elevated heat stress risk, these systems could activate preemptively, maintaining optimal conditions for the herd and thereby minimizing the physiological and productive impacts of heat stress.

In essence, the practical application of our linear model in dairy management software and sensoring platforms represents a significant leap forward in precision livestock farming. It embodies a shift towards more data-driven, proactive approaches to herd management, where the emphasis is on preventing stressors rather than merely responding to their consequences. Such advancements not only promise to enhance dairy cow welfare and farm profitability but also contribute to the sustainability of milk production in the face of changing global climates. While the development and implementation of our linear model for analyzing panting behavior in dairy cows under various environmental and physiological variables mark significant progress in the domain of precision livestock farming, the process was not without its limitations. These limitations highlight areas for improvement and future exploration, ensuring the ongoing refinement and applicability of predictive models in dairy management.

One notable limitation encountered during the model-building process was the substantial computational resources required to analyse large datasets. The complexity and volume of data generated in modern dairy operations, encompassing detailed records of environmental conditions, animal behaviors, and physiological metrics, necessitate high-performance computing (HPC) solutions. These advanced computational capabilities are essential for processing and analysing the data efficiently but may not be readily accessible to all researchers or farm operations, potentially limiting the widespread adoption of such data-driven approaches.

Additionally, the construction of our linear model underscored the critical need to scrutinize the multivariable roles and the quality of data involved in the building process. The interplay between different variables, such as THI, temperature, humidity, rumination, ingestion, and panting behavior, requires careful consideration to ensure the model accurately captures the complex relationships influencing heat stress and its impacts. Moreover, data quality—encompassing accuracy, completeness, and consistency—emerges as a pivotal factor that directly influences the model's reliability and predictive power. Ensuring high-quality data input is therefore paramount, necessitating rigorous data collection, validation, and preprocessing practices.

Furthermore, while the linear model provides valuable insights into the dynamics of heat stress and its effects on dairy cows, exploring its foundational relationships within more complex predictive model structures, such as neural networks (NN) and random forests, presents an intriguing avenue for future research. These advanced modeling techniques, known for their ability to handle nonlinear relationships and interactions among a large number of variables, could potentially offer more nuanced and accurate predictions. Evaluating the basic relationships identified by the linear model in the context of these sophisticated models may not only enhance predictive accuracy but also uncover deeper insights into the mechanisms of heat stress and its mitigation.

In conclusion, while the limitations encountered in the model-building process, including the need for HPC resources, the imperative for careful review of multivariable roles and data quality, and the potential benefits of integrating the model into more complex predictive structures, present challenges, they also outline a roadmap for future advancements. Addressing these limitations will not only improve the model's applicability and effectiveness but also contribute significantly to the field of precision livestock farming, ultimately benefiting dairy cow welfare and productivity.

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