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Algorithmic Module in Integrated Farm Systems for Reducing Antimicrobial Resistance in Livestock Production

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Introduction

Recognising the importance of the cattle sector in the European Union is an essential starting point for developing farm-level strategies as well as for shaping the new Common Agricultural Policy, particularly in the context of production sustainability and food safety. This sector is closely linked to environmental challenges and potential risks to public health, including the spread of antimicrobial resistance (Ilea, 2009; Havlík et al., 2014). Cattle production represents a significant source of environmental pressures occurring across temporal and spatial scales, and its impact on climate change has become a subject of intensive scientific and policy interest (Caro et al., 2014).

The diversity of farms and production systems within the EU results in substantial differences in environmental, production, and animal health indicators. Research indicates that the transition from extensive and poorly managed systems to more efficient, technology-supported, and well-managed production models can contribute to reducing greenhouse gas emissions, improving animal health management, and rationalising antibiotic use (Havlík et al., 2014; Peyraud et al., 2020). In this context, integrated farm systems and algorithmic approaches to herd management are gaining importance, as they enable systematic data collection and evaluation related to production, animal health, and environmental parameters, thereby creating the conditions necessary to minimise the risk of antimicrobial resistance.

From an economic perspective, ensuring the long-term sustainability and profitability of the cattle sector in the European Union is equally essential. Major challenges are associated with significant heterogeneity among Member States in terms of farm income, structural characteristics, and applied husbandry practices (Hocquette et al., 2018). Therefore, promoting efficient, environmentally sustainable, and data-driven management models is crucial not only for environmental protection but also for animal health, food safety, and the control of antimicrobial resistance, which together form the central framework of this publication.

1 History of Animal Production

1.1 History of Meat Production

The history of cattle breeding dates back to the Neolithic Revolution, approximately 11,000 years ago, when humans began domesticating animals (Reed, 1984; Benecke, 1994). Domestication represented a fundamental turning point in human development, as it enabled the systematic acquisition of meat, milk, hides, and later draft power (Reed, 1984; Mason, 1984). Animals received regular feeding and protection, while humans gained easier access to food and materials without the need for hunting.

In ancient Egypt and Greece, cattle were housed in barns equipped with drainage systems and individual feeding spaces comparable to modern housing standards (Benecke, 1994). Roman authors such as Varro and Columella described cattle husbandry practices and recommended barns with perforated floors for urine and manure drainage, adequate space for animals, and protection from cold. The number of livestock gradually increased, reducing the importance of hunting and fishing as primary food sources (Benecke, 1994).

In the Middle Ages (6th–15th century), cattle were mainly kept outdoors on pastures, meadows, or near forests close to villages (Benecke et al., 2003). With the development of agriculture, three-field crop rotation systems enabled more efficient land use while limiting grazing areas. Cattle breeding became the basis for milk and meat production. During winter, animals were housed and fed hay and small branches to ensure sufficient nutrition during cold months (Falkenberg and Hammer, 2006).

In the Early Modern period (16th–18th century), livestock production was closely linked with progress in crop production and the introduction of crop rotations. These systems enabled more efficient land use, systematic feed production, and the preparation of specialised summer pastures. Cattle breeding gradually moved from traditional pastures to housing facilities, particularly in winter, allowing better control of animal nutrition and health (Comberg, 1984).

In the 18th century, Europe was struck by waves of cattle plague that killed millions of animals (Nusshag, 1954). For example, 395,000 animals died in the Netherlands, 116,277 in East Frisia, and 255,000 in Denmark. In England, 80,000 suspected and diseased animals were culled between 1754–1755, stopping the epidemic (Nusshag, 1954). These events led to the emergence of veterinary medicine and the establishment of veterinary schools, for example in Hanover in 1778 (Comberg, 1984). Prominent scientists such as Albrecht Daniel Thaer and Johann Christian Polycarp Erxleben emphasised the importance of proper housing, appropriate stocking density, and adequate access to light and air for cattle health (Comberg, 1984).

In the 19th and early 20th centuries, cattle numbers in Germany increased from 10 million in 1800 to approximately 21 million in 1913 (Comberg, 1984). Intensification of cattle production was associated with increased dairy and meat productivity, while the number of farms declined and production focused on higher efficiency (Bäuerle and Tamásy, 2012).

Today, livestock production is characterised by intensification and specialisation (Hartung, 2000). Cattle are often housed year-round, with high stocking density, mechanisation, and automation of feeding, watering, manure removal, and ventilation. Consumers emphasise animal welfare, food safety, and sustainability, which influence housing and grazing systems (Hartung, 2000). The future of cattle production depends on cooperation among farmers, scientists, veterinarians, and consumers and on the implementation of systems ensuring animal health and welfare, environmental sustainability, and economic efficiency (Hartung, 2012).

Modern systems also include free housing systems for dairy and beef cattle. Consumers increasingly demand sustainable livestock production that combines economic benefits, animal welfare, safe food, and environmental protection (Hartung, 2000; Hartung, 2012).

Table 1 Overview timeline of the history of meat production

Period / years	**Main events / development**
≈ 2.5 million years BC	First evidence of meat consumption by prehistoric humans (hunting, scavenging).
≈ 10,000 BC	Neolithic Revolution – domestication of livestock; beginning of targeted meat production.
≈ 5,000–3,000 BC	Ancient civilizations – drying and salting meat as preservation methods.
≈ 1,000 BC	Development of livestock breeding; meat becomes an important part of elite diets.
1st–5th century AD	Ancient Greece and Rome – production of sausages and fermented meat products.
5th–15th century	Middle Ages – meat mainly a luxury food; salting, smoking, butcher guilds.
16th–18th century	Early Modern period – development of regional meat specialties.
19th century	Industrial Revolution – mechanized slaughterhouses and meat preservation.
Early 20th century	Introduction of refrigeration technologies and hygiene regulations.
1950–1980	Intensification of livestock production; mass production of meat products.
1980–2000	Development of food microbiology and emphasis on meat safety.
21st century	Globalization of meat production; focus on sustainability and alternatives.

Source: Pearson et al., 1997; Speedy, 2003; McGee 2007; Montanari, 2013

1.2 History of Dairy Production

Milk and dairy production is among the oldest forms of animal domestication and utilisation of animal products by humans. Archaeological findings and historical sources indicate that the domestication of ruminants, particularly cattle, sheep, and goats, began approximately 10,000 years ago in the Middle East and Southeastern Europe. These animals provided not only meat and hides but also milk, which became an important source of nutrition, especially for populations with limited access to other protein sources (Zeder et al., 2008; Vigne et al., 2011).

During antiquity and the Middle Ages, milk was mostly consumed fresh or fermented in the form of traditional products such as yogurt, kefir, and various types of cheese. Fermentation served not only to improve flavour but primarily as a method to extend shelf life and reduce the risk of diseases caused by microorganisms. In some cultures, specific traditional cheeses developed and became part of cultural heritage and regional gastronomy (Fox et al., 2017).

The first technological breakthrough in the history of dairy production was mechanised milking and the emergence of dairy plants in the 19th century. Industrialisation enabled more systematic production, collection, and distribution of milk, reducing contamination risks and improving the availability of dairy products for urban populations. During this period, the first forms of pasteurisation were also developed, gradually becoming a standard in modern dairy technologies (Walstra et al., 2006).

In the 20th century, advances in microbiology and food technology became crucial for ensuring milk safety. The introduction of pasteurisation and strict hygiene standards enabled the mass distribution of milk without significant risk of pathogen transmission. At the same time, the production of diverse dairy products expanded, from cheeses and yogurts to butter, cream, and other processed products. Modern processing, storage, and quality monitoring methods ensure consistent safety and nutritional value of dairy products in the global market (Jay et al., 2005).

The history of milk production therefore reflects not only technological progress and the development of food safety but also the cultural, economic, and social aspects of animal product utilisation. Knowledge from the past is essential for understanding current principles of milk production, hygiene, and quality, which form the basis of modern food safety systems (FAO & WHO, 2004).

Table 2 Overview timeline of the history of dairy production

Period	Main events / development
10,000 years ago	Domestication of ruminants (cattle, sheep, goats) in the Middle East and Southeastern Europe; beginning of milk use as food.
Antiquity (3000–500 BC)	Consumption of fresh milk and fermented products (yogurts, cheeses); emergence of early dairy traditions.
Middle Ages (500–1500 AD)	Development of traditional cheeses and fermented dairy products; processing to extend shelf life and reduce microbial risk.
19th century	Industrialization of dairy production: mechanized milking, dairy plants, development of milk distribution to cities; early forms of pasteurization.
Early 20th century	Development of microbiology and food technology; systematic pasteurization and hygiene standards; increased safety of milk and dairy products.
Second half of the 20th century	Mass production of milk and dairy products; development of diverse products (cheese, yogurt, butter, cream); modern storage and quality monitoring methods.
21st century	Globalization of dairy markets; advanced processing, packaging, and quality tracking technologies; focus on food safety, nutritional value, and sustainability.

Source: Jay et al., 2005; Zeder et al., 2008; Vigne et al., 2011; Fox et al., 2017

2 Cattle Farming

Cattle farming is important mainly because of its production outputs such as milk and meat. As the global population continues to grow, the demand for cattle production naturally increases as well. Cattle farms are essential for agriculture and the economy. According to official statistics from the Food and Agriculture Organization (FAO), there are over 1.5 billion head of cattle worldwide. Among countries, Brazil ranks first with a total share of 15%, where more than 211 million head of cattle are raised. Brazil's leading position is certainly no coincidence, as this country has long been one of the largest exporters of beef in the world. The second-largest country, with over 190 million head of cattle, is India, accounting for about 13% of the total. The methods of cattle farming in India are significantly influenced by Hinduism, which considers the cow a sacred animal, and in many parts of India, there are severe penalties for killing cows. On the other hand, India is known for its wide variety of cattle breeds that are not raised anywhere else. The third-largest cattle-farming country is China, where large farms are being built. Cattle farming in China is experiencing rapid growth, with over 113 million head of cattle raised. Interestingly, China is also home to the world's largest dairy farm, which impresses not only with its size but especially because it houses over 100,000 dairy cows. The top five countries with the largest cattle populations are completed by the USA in fourth place

(which is still the largest producer of beef) and, surprisingly, Ethiopia in fifth place. For comparison, according to the FAO ranking, Slovakia ranks 125th with a cattle population of 430,000 head (FAO, 2025).

2.1 Primary Meat Production

Meat plays an important role in human nutrition as a concentrated source of high-quality proteins and essential amino acids necessary for growth, tissue repair, and maintenance of muscle mass. It is also an important source of micronutrients that are less available or less bioavailable in plant-based diets, particularly vitamin B12, iron, zinc, and selenium. When consumed in appropriate amounts, meat contributes to dietary adequacy, especially in children, pregnant women, and older adults (FAO, 2023). Beef cattle production therefore represents an important component of livestock production, as it is focused on beef as a key food commodity. An important aspect is the relationship between breed and beef quality. Beef breeds are often associated with higher meat quality compared to dairy breeds. Genetic selection has led to clear differentiation between beef and dairy breeds, with beef breeds tending to produce meat with higher intramuscular fat content, more pronounced marbling, and better flavour (Park et al., 2018; Sakowski et al., 2022; Kostusiak et al., 2023; Tan and Jiang, 2024; Papanikolopoulou et al., 2025).

2.1.1 Beef Cattle Breeding

Beef breeds, such as Angus, exhibit stronger marbling and higher intramuscular fat due to earlier physiological maturity and genetic predisposition for fat deposition. Breeds that reach slaughter maturity earlier deposit fat within muscles sooner, increasing marbling as well as meat juiciness and flavour (Kostusiak et al., 2023). In contrast, breeds that mature later may produce leaner meat at the same slaughter age because intramuscular fat deposition occurs later (Tan and Jiang, 2024).

The structure of muscle tissue and connective tissue content, influenced by genetic selection for meat production, also contribute to greater tenderness in beef breeds compared to dairy breeds (Herrera et al., 2018). Beef breeds are typically characterised by muscle structure associated with higher tenderness, whereas dairy breeds often have higher connective tissue content, resulting in firmer meat (Warner et al., 2021).

High intramuscular fat content and marbling are considered important indicators of visual appeal and sensory properties of meat, with beef breeds such as Angus achieving higher

values compared to later-maturing or primarily dairy breeds (Park et al., 2018; Sakowski et al., 2022).

The start of breeding and specialisation in meat cattle production worldwide reflected specific geographic, climatic (forage-based), economic, and social conditions. These included conditions unfavourable for intensive dairy cattle breeding, extensive farming, large pasture areas, sparsely populated regions, and distant dairies. Several literature sources indicate that the origins of major meat cattle breeds date back to England, from where they later spread globally. Most of today's specialised meat breeds evolved from originally multi-purpose breeds. According to global statistics, there are over 250 meat cattle breeds worldwide, with as many as 60 raised in the USA. For better clarity, breeds used for meat production are categorised into groups based on various criteria. The classification of breeds considers their origin, breeding intensity, and body frame size (Cozzi, 2011).

English breeds of small to medium body frame (Hereford, Aberdeen Angus):

These breeds excel in adaptability, resilience, and grazing ability. Compared to continental breeds, they tend to mature earlier. These breeds are not characterised by extremely high growth rates or pronounced muscle development, but they are known for good reproduction, easy calving, and a high number of calves raised. During finishing, they efficiently use roughage, and the carcass has a higher proportion of fat. This means they are not finished to high slaughter weights, but the muscle tissue has a higher content of intramuscular fat (so-called marbling). Besides their country of origin, these breeds are also widespread in countries such as the USA, Canada, Brazil, Argentina, as well as Australia and Japan, where they are mainly valued for their marbled meat. Aberdeen Angus is one of the most widely raised breeds in the world (Zigo et al., 2022).

Continental breeds can be divided into two larger groups:

- **French breeds** of large body frame (Charolais, Blonde d'Aquitaine), which are characterised by high growth rates to higher weights and body dimensions. Their excellent meat production performance is reflected in high weight gains, significant muscling of important meat parts, and high carcass yields. They are fed to higher slaughter weights mainly through intensive methods, which means they require more nutrition and feeding. They are characterised by producing lean meat with low fat deposition.

- **Continental breeds** of medium to larger body frame (Limousin, Meat Simmental, Piemontese, Belgian Blue, and others). Most of these breeds were originally raised for versatility and utility. These breeds also have very good muscle development and high carcass yield (Griffon et al., 2017).

Extensive, rustic, and hobby breeds (Galloway, Salers, Gascon, Aubrac, Scottish Highland cattle, and others). These breeds are known for their resistance to harsh weather conditions and require minimal shelter, even during winter. Their meat is recognised for its unique flavour qualities. They are often raised for their attractive appearance, which is part of the strategy for many rural tourist centres, helping to preserve the characteristic landscape of remote, hard-to-reach pastures. Many are kept as genetic reserves or as part of cultural and natural heritage (Bureš and Bartoň, 2010).

Some authors describe a significant group of Oriental breeds involved in beef production in regions of Asia and Africa. Since the 19th century, breeds originating from the Indian buffalo (Bos indicus) – zebu, or Brahman – have been imported into South America and North America. The so-called zebuine breeds raised in tropical areas are characterised by their resistance to drought, heat, sunlight, and parasites (Felius et al., 2011).

A significant production trait of beef breeds is a high growth rate with pronounced muscle development and economically efficient meat production. In the European Union, veal production primarily uses crossbreeds of dairy and beef breeds, such as Holstein x Belgian Blue, or purebred beef breeds like Belgian Blue (Pardon et al., 2014). Specialised beef breeds allow for achieving higher slaughter weights, but their use for veal production is less economically advantageous because the goal is meat with lower slaughter weights and a fine texture (Lengyel et al., 2003).

Angus is a beef breed characterised by early attainment of slaughter maturity and a genetic predisposition to higher deposition of intramuscular fat (Sakowski et al., 2022; Papanikolopoulou et al., 2025). The meat of this breed achieves the highest marbling among beef breeds (27.01% ± 12.09), while the total fat content in muscle is 5.35% ± 2.61. Angus is also characterised by higher tenderness, with compression force of 48.04 N ± 23.30 and shear force of 15.42 N ± 6.12. The fatty acid profile is favourable for flavour and health aspects, with a higher proportion of monounsaturated fatty acids (C18:1n-9 + n7 = 35.9%) and a lower proportion of linoleic acid (C18:2n-6 = 7.87%) (Papanikolopoulou et al., 2025).

Charolais is a French beef breed with a large body frame and high growth potential, characterised by later attainment of slaughter maturity compared with Angus, but with a

significantly higher proportion of muscle mass (Indurain et al., 2009; Hocquette et al., 2011). Charolais meat is characterised by lower marbling (9.84% ± 4.21) and lower total intramuscular fat content, approximately 2.10% ± 0.85. On the other hand, it achieves higher carcass yield, typically ranging from 62–65%, and a higher proportion of valuable muscle cuts. Meat tenderness is lower compared with Angus, reflected in higher compression force (72.18 N ± 18.64) and shear force (23.67 N ± 7.45), especially at shorter ageing periods. The fatty acid profile of Charolais meat is characterised by a lower proportion of monounsaturated fatty acids (C18:1n-9 + n7 = 29.4%) and a higher proportion of polyunsaturated fatty acids, particularly linoleic acid (C18:2n-6 = 12.3%) (Indurain et al., 2009).

Limousin, in terms of carcass characteristics, is characterised by a very high proportion of muscle and a low degree of carcass fatness due to genetic predisposition for efficient muscle deposition. Intramuscular fat content is lower compared with Angus or Hereford breeds and generally ranges from 1.8–2.5%, leading to lower marbling but very favourable carcass yield of 62–66% (Albertí et al., 2008; Hocquette et al., 2011). Limousin meat is characterised by fine muscle fibres and relatively good tenderness, with shear force values after standard ageing ranging from 20–24 N. The fatty acid profile shows lower monounsaturated fatty acids (C18:1n-9 approximately 28–30%) and relatively higher polyunsaturated fatty acids, particularly linoleic acid (C18:2n-6 approximately 11–13%) (Hocquette et al., 2011; Realini et al., 2014;).

Beef Simmental is characterised by a balanced ratio of muscle and fat. The average intramuscular fat content ranges from 2.8–3.6%, ensuring good sensory quality without excessive carcass fatness (Albertí et al., 2008). Marbling is considered moderate, and meat maintains favourable tenderness with shear force values ranging from 18–22 N after appropriate ageing. The fatty acid profile shows balanced monounsaturated fatty acids (C18:1n-9 approximately 30–32%) and relatively higher polyunsaturated fatty acids (Realini et al., 2014).

Hereford, in terms of carcass characteristics, is characterised by a higher degree of carcass fatness and pronounced intramuscular fat deposition, which is reflected in good meat marbling. Intramuscular fat content typically ranges from 4.0–5.5%, depending on the finishing system and duration of the finishing period (Hocquette et al., 2011). Meat from the Hereford breed achieves good tenderness, with shear force values most commonly ranging between 15–19 N, placing it among breeds with favourable sensory evaluation. Higher fat deposition is also reflected in a greater proportion of monounsaturated fatty acids, particularly oleic acid (C18:1n-9), which may account for 34–36% of the total fatty acid spectrum, while the proportion of linoleic acid (C18:2n-6) is lower compared with breeds with lower fat reserves. These

characteristics positively influence flavour, juiciness, and overall acceptability of the meat, particularly in extensive pasture-based production systems (Smith et al., 2009).

Belgian Blue, in terms of carcass characteristics, is among the most heavily muscled cattle breeds, which is reflected in an exceptionally high proportion of muscle and a very low degree of carcass fatness. Carcass yield typically ranges from 65–70%, while the proportion of valuable muscle cuts is significantly higher compared with conventional beef breeds (Albertí et al., 2008). Intramuscular fat content is very low and most often does not exceed 1.0–1.5%, resulting in minimal meat marbling. Meat from the Belgian Blue breed is characterised by very fine muscle fibres, low connective tissue content, and good tenderness, with shear force values after an adequate ageing period ranging from 18–22 N despite the low fat content. The fatty acid profile of the meat is characterised by a low proportion of monounsaturated fatty acids (C18:1n-9 approximately 26–28%) and a relatively higher proportion of polyunsaturated fatty acids, particularly linoleic acid (C18:2n-6 approximately 13–15%), which increases the nutritional value of the meat but may reduce its sensory juiciness and flavour intensity (Realini et al., 2014).

Chianina, another beef breed, is primarily known for its bright meat colour (L* = 34.79 ± 5.30, a* = 26.64 ± 3.02, b* = 23.49 ± 3.24). Marbling is moderate (14.60% ± 6.28), while the total fat content is the highest among beef breeds (6.30% ± 1.94). Chianina meat shows lower tenderness in compression (66.18 N ± 21.61) and shear force of 15.24 N ± 6.49. The fatty acid profile shows a low proportion of omega-3 fatty acids (C18:3n-3 = 0.59%) and a high proportion of stearic acid (C18:0 = 18.2%) (Sakowski et al., 2022; Papanikolopoulou et al., 2025).

Holstein is primarily a dairy breed; however, its muscle shows the second highest total fat content (5.81% ± 2.48) and a red, bright meat colour (L* = 33.78 ± 1.26, a* = 22.44 ± 2.04, b* = 21.00 ± 1.94). Holstein is one of the most tender breeds, with compression force of 43.44 N ± 18.75 and shear force of 15.26 N ± 6.63. The fatty acid profile is characterised by a higher proportion of omega-6 fatty acids (C18:2n-6 = 15.7%) and a lower proportion of monounsaturated fats (C18:1n-9 + n7 = 27.7%), with a large proportion of fat being invisible (Warren et al., 2008).

German Red Pied is a beef breed with weaker marbling (11.80% ± 4.96) and low total fat content (3.09% ± 0.67). Meat from this breed is darker (L* = 27.64 ± 3.24, a* = 19.71 ± 2.11) and shows higher tenderness in terms of shear force (12.98 N ± 5.16), although compression force reaches 53.35 N ± 17.77. The fatty acid profile contains a higher proportion

of C17:1 and monounsaturated fatty acids (C18:1n-9 + n7) compared with Holstein (Sakowski et al., 2022; Papanikolopoulou et al., 2025).

Piemontese is a beef breed with weaker marbling (10.23% ± 4.05) and the lowest total fat content (2.63% ± 0.44). The meat is darker (L* = 26.39 ± 3.18, a* = 19.55 ± 2.11), with a higher proportion of omega-3 fatty acids (C18:3n-3 = 0.92%) and a lower proportion of omega-6 fatty acids (C18:2n-6 = 10.2%). Meat tenderness shows compression force of 59.23 N ± 22.17 and shear force of 15.22 N ± 6.69 (Sakowski et al., 2022; Papanikolopoulou et al., 2025).

Polish crossbreed represents crossbred cattle with stronger marbling (18.83% ± 5.75) and medium total fat content (4.81% ± 1.62). The meat is red and bright (L* = 31.89 ± 2.95, a* = 21.37 ± 2.11, b* = 18.92 ± 2.33) and simultaneously the toughest in compression (63.23 N ± 18.71) and shear force (21.62 N ± 8.86). The fatty acid profile contains a high proportion of omega-6 fatty acids (C18:2n-6 = 13.8%) (Sakowski et al., 2022; Papanikolopoulou et al., 2025).

In some countries, local meat breeds with a protected designation of origin (PDO) or protected geographical indication (PGI) are used, which provide unique organoleptic properties to the meat. For example, in France, breeds such as Limousine, Blonde d'Aquitaine, and Bazadaise are used; in Portugal, the Mertolenga and Mirandesa breeds; and in Spain, local crossbreeds of breeds for the production of veal „ternera" (Revilla and Vivar-Quintana, 2006; Monteiro et al., 2013).

Meat breeds are often combined with dairy breeds when raising calves to achieve an optimal balance between growth, meat quality, and economic efficiency (Ngapo and Gariépy, 2006; Bureš and Bartoň, 2010).

2.1.2 Factors Affecting Beef Production Performance

Beef production performance in cattle, expressed through growth capacity, feed conversion efficiency, carcass yield, and carcass quality, is the result of a complex interaction of genetic, physiological, and production factors. From a **genetic perspective**, breed, sex, age, and the individual genetic potential for muscle growth and fat deposition play a decisive role, directly influencing body weight, muscling, and carcass composition. Differences among breeds and genetic lines significantly affect not only growth rate but also the muscle-to-fat ratio, while these effects are further modulated by the production system and nutrition. Beef quality, including tenderness, juiciness, and sensory attributes, is closely linked to the degree of fatness and marbling, which are determined by genetic factors in combination with nutrition and finishing management, requiring a comprehensive approach to beef production management (Nguyen et al., 2021; Clinquart et al., 2022).

From a **nutritional and technological perspective**, feed efficiency represents a key factor that fundamentally affects both the economics of finishing and the environmental sustainability of beef production. Improvements in feed conversion can be achieved through a combination of precise ration formulation, optimisation of the energy-to-protein ratio, and the selection of animals with higher production efficiency. Modern approaches include the use of genomic tools and detailed monitoring of feed intake, enabling targeted increases in growth with lower nutrient consumption. At the production-system level, strategies integrating genetics, nutrition, and management have proven effective, leading to more stable growth curves and improved feed conversion throughout the entire finishing period (Terry et al., 2020; Ojo et al., 2024).

Animal health and welfare have a direct impact on beef production performance, as diseases and stress factors reduce feed intake, impair nutrient utilisation, and prolong the finishing period. Of particular importance is bovine respiratory disease complex, which is among the main causes of morbidity in feedlot systems and is associated with reduced weight gains and losses in carcass weight. Disease prevention through biosecurity, vaccination programmes, and the minimisation of stress during transport and mixing of animals is therefore an integral component of strategies aimed at improving beef production performance. In addition to health risks, the importance of environmental stressors, particularly heat stress, is increasing, as it negatively affects growth, welfare, and production stability of cattle and, in the long term, also carcass and meat quality parameters (Thornton et al., 2022; O'Donoghue et al., 2025).

2.1.3 Determinants of Beef Production and Quality

Beef production is influenced by breed genetics, nutritional management, and production conditions (Warner et al., 2021). Beef breeds are specifically selected for higher muscle growth and intramuscular fat deposition, which contributes to improved meat quality (Papanikolopoulou et al., 2025). In contrast, dairy breeds, which are not primarily selected for muscle production, tend to produce meat with lower fat content and a different texture (Warren et al., 2008).

The growth rate and maturity of a breed also influence the amount and distribution of fat in muscle tissue. Beef breeds that reach slaughter maturity earlier deposit intramuscular fat sooner, resulting in higher marbling and improved sensory quality of meat (Sakowski et al., 2022; Papanikolopoulou et al., 2025). Breeds that mature more slowly may produce leaner meat at the same slaughter age because fat deposition occurs later (Liu et al., 2022).

Muscle tissue of beef breeds is often characterised by greater tenderness and better sensory quality due to an optimal ratio of muscle to connective tissue. Different breeds also exhibit varying proportions of unsaturated and saturated fatty acids, which may influence flavour, juiciness, and nutritional value of meat (Warner et al., 2021; Herrera et al., 2018).

From a production perspective, it is important to optimise feeding regimes, slaughter age, and herd management in order to maximise meat quality while maintaining efficient production. In this way, it is possible to produce meat with consistent characteristics that meet market requirements and consumer expectations (Sakowski et al., 2022; Papanikolopoulou et al., 2025).

Beef production represents an important, although relatively smaller, share of total meat production in the European Union. In 2024, the EU produced approximately 6.6 million tonnes of beef and veal, representing an increase of about 3.1% compared with the previous year and ending a five-year decline in production. The six main beef-producing countries in the EU were France, Germany, Poland, Ireland, Italy, and Spain, with Poland accounting for approximately 11.1% of EU production (EUROSTAT, 2025).

Within the countries of the Visegrad Group (V4), beef production plays an important, although differently scaled, role in each state. Poland is the dominant beef producer in the region, with an estimated annual production of around 560,000 tonnes, most of which is intended for export within the European Union. This export-oriented profile reflects a robust agri-food infrastructure and the ability to meet not only domestic demand but also compete on the EU internal market.

In the Czech Republic, Slovakia, and Hungary, beef production is generally lower than in Poland and is primarily oriented towards the domestic market and regional consumption. Historical analyses of self-sufficiency indicate that these countries are capable of covering their own beef consumption through domestic production, although their production volumes are smaller and strategic decisions in cattle breeding and processing may influence the balance between production, consumption, and trade.

Self-sufficiency in beef production differs among the V4 countries. While Poland achieves high levels of self-sufficiency and a surplus available for export, Slovakia, the Czech Republic, and Hungary traditionally focus more on meeting domestic demand, and their markets may also be influenced by changes in consumer preferences, feed prices, and support policies for cattle breeding within the EU Common Agricultural Policy (Slaboch and Kotyza, 2016).

The overall context of beef production in the V4 therefore reflects a combination of Poland's strong production position, stable but smaller production in the Czech Republic, Slovakia, and Hungary, and the important role of these countries within the broader European beef market. These differences are important when evaluating their economic and trade strategies in beef production in the 21st century (EUROSTAT, 2025).

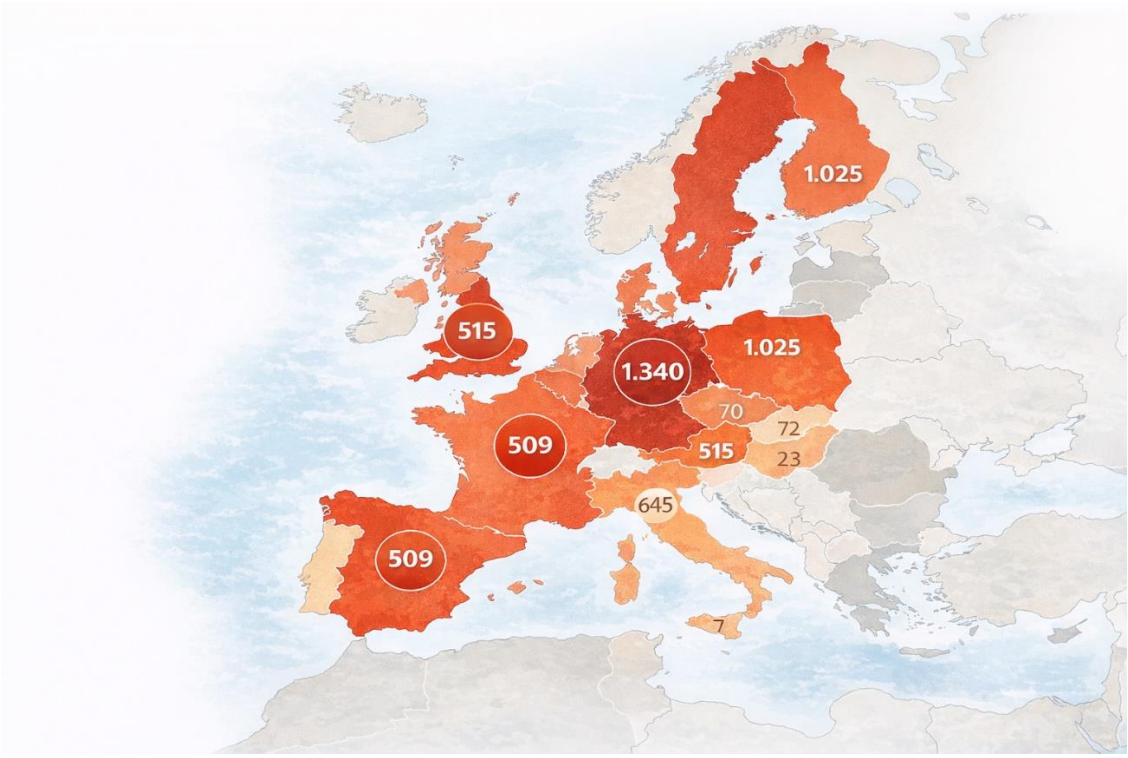


Figure 1 Current beef production in Europe

The numerical values shown for individual countries represent the volume of beef production in thousand tonnes of carcass weight.

Source: Author's own elaboration based on EUROSTAT data (EUROSTAT, 2025)

Veal in the EU is defined as meat from cattle younger than 8 months (category V), while beef is meat from animals older than 12 months (EU, 2013). In practice, a distinction is made between white veal, obtained from calves fed milk or milk replacers, characterised by low iron content and a pale pink muscle colour, and rosé veal, with a slightly red colour, which may be fed a mixed diet including cereals (European Commission, 2003; Pardon et al., 2014).

Table 3 Fattening systems used in the production of beef and veal in the EU and outside the EU

Country / Region	Meat type	Category	Fattening system / note
France	Veal	White veal	Dairy × beef crossbreeds, white veal production
France	Veal	Rosé veal	Fed milk and cereals, pink colour
Netherlands	Veal	White/rosé	90% of production exported, dairy breeds
Belgium	Veal	White veal	Dairy breeds, white veal production
Italy	Veal	White/rosé	Regional PDO/PGI products
Spain	Veal	Ternera	Local breeds, combined feeding system
USA / Canada	Veal	Bob veal	Milk- or grain-fed, young calves
Australia / NZ	Veal	Veal	Bob veal or older calves
EU (average)	Beef	Beef	Intensive, extensive, or organic finishing

Source: European Commission, 2003; Lengyel et al., 2003; Ngapo and Gariépy, 2006; Revilla and Vivar-Quintana, 2006; Brown and Claxton, C., 2011; Hocquette and Chatellier, 2011; Monteio et al., 2013; Pardon et al., 2014; EUROSTAT, 2015; MLA, 2017

Beef cattle finishing systems include intensive finishing with controlled diets, extensive finishing with access to natural feed resources, and organic finishing focused on environmentally friendly production (UNECE, 2011). In the Netherlands, calves are raised exclusively for white or rosé veal, with 90% of production intended for export. In Belgium, white veal from dairy breeds predominates, while France and Italy combine different finishing systems and breeds, including regional PDO and PGI products (Ngapo and Gariépy, 2006; Monteiro et al., 2013).

In non-European countries such as the USA, Canada, Australia, and New Zealand, production is mainly focused on bob veal, meaning calves slaughtered within a few weeks after birth; in Canada, calves are fattened with milk or cereals up to 5–7 months of age to a weight of 200–318 kg (Brown and Claxton, 2011; MLA, 2017).

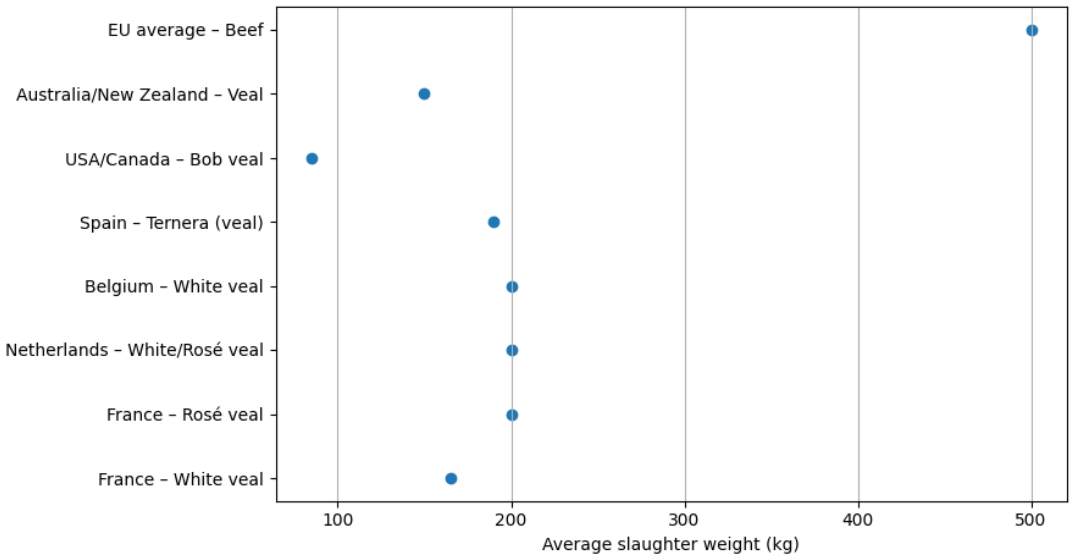


Figure 2 Average slaughter weights: veal types and beef

Source: Author's own elaboration based on Brown and Claxton, C., 2011, European Commission, 2003, EUROSTAT, 2015, MLA, 2017.

2.1.4 Benefits of Beef and Meat Product Consumption for Human Health

Beef is one of the most important foods of animal origin in terms of nutritional value and the bioavailability of essential nutrients. It is a rich source of high-quality proteins with a complete spectrum of essential amino acids that are necessary for growth, tissue regeneration, maintenance of muscle mass, and proper immune system function. Compared with many plant sources, beef provides **proteins** with high digestibility and a favourable **amino acid profile**, which is particularly important for older adults, physically active individuals, and populations with increased protein requirements (De Smet, 2024; Stadnik, 2024).

From a **micronutrient** perspective, beef is one of the most significant sources of **heme iron**, whose bioavailability is substantially higher than that of non-heme iron from plant foods. Adequate iron intake is crucial for the prevention of anaemia, proper muscle function, and cognitive processes. In addition to iron, beef contributes significantly to **zinc** intake, which plays a fundamental role in immune responses, wound healing, and hormonal regulation, as well as **selenium**, an important antioxidant. Particularly important is the content of **vitamin B12**, which is virtually absent in plant foods and is essential for the nervous system and haematopoiesis. Current nutritional analyses indicate that including beef in a balanced diet significantly reduces the risk of deficiencies of these micronutrients in the population (Boutron-Ruault et al., 2017; Dhakal et al., 2025).

Beef is also a source of several bioactive compounds such as **creatine, carnosine, anserine**, and **taurine**, which are involved in muscle energy metabolism, regulation of oxidative stress, and the buffering capacity of muscle tissue. These compounds are particularly important for maintaining muscle function and physical performance, and their intake from beef may have a positive impact on the prevention of sarcopenia in older populations. Recent review studies emphasise that these bioactive components represent one of the main differences between beef and plant-based alternatives, which either do not contain them or contain them only in negligible amounts (Leroy, 2023; Stadnik, 2024).

From an overall health perspective, however, it is important to emphasise that the health benefits of beef depend on the amount, frequency of consumption, and processing methods. Current scientific evidence suggests that moderate consumption of fresh, minimally processed beef as part of a balanced diet does not pose a health risk and may contribute to improved nutritional adequacy. In contrast, excessive consumption of highly processed meat products with high levels of salt, saturated fat, and additives may be associated with an increased risk of cardiometabolic diseases. Modern nutritional recommendations therefore emphasise beef quality, appropriate technological processing, and its inclusion in a diverse dietary pattern as key factors for maximising health benefits (De Smet, 2024; Dhakal et al., 2025).

Overall, it can be concluded that beef, when consumed in a reasonable and targeted manner, represents a significant contribution to human health, particularly in terms of providing high-quality proteins, bioavailable minerals, and bioactive compounds. Its role in the diet is especially important for populations with increased nutritional requirements, and health benefits can be achieved particularly when beef is part of a balanced diet rather than the dominant component of the diet (Leroy, 2023; Stadnik, 2024).

2.2 Primary Milk Production

Dairy cattle breeding plays an important role in the agricultural production system, as it represents the main source of raw cow's milk intended for further processing and consumption. The level of breeding success is determined by the ability of breeds to produce milk efficiently and over the long term while maintaining physiological balance, reproductive performance, and overall animal fitness. In modern production systems, increasing emphasis is placed not only on production quantity but also on the sustainability of dairy farming and dairy cow welfare.

Dairy breeds differ from other production types through specific body conformation, metabolic requirements, and functional traits that are the result of targeted genetic selection.

Breeding programmes focus on improving milk yield in combination with resistance to production diseases, efficient feed utilisation, and the ability to adapt to different farming conditions. These characteristics enable dairy breeds to fulfil their production function not only in intensive systems but also in alternative and combined farming systems, including dual-purpose breeding programmes (Lassala et al., 2023).

2.2.1 Breeding of Dairy Cattle Breeds

The aim of breeding is to achieve a high milk yield while maintaining good animal health, reproductive performance, and longevity. In addition to milk production, these breeds also provide genetic material for breeding and interdisciplinary use (e.g., dual-purpose programmes). Dairy breeds are characterised by typical conformation traits that are the result of long-term breeding efforts aimed at maximising milk production while maintaining body condition and functional resistance to diseases (Lassala et al., 2023).

Dual-purpose breeding programmes represent a system in which cattle are bred and raised to achieve satisfactory milk production in dairy cows together with good growth and carcass traits in offspring. Key characteristics of dual-purpose programmes:

- medium to high milk yield (lower than in specialised dairy breeds),
- better muscling and meat yield compared with purely dairy breeds,
- higher robustness, longevity, and reproductive performance,
- suitability for extensive and mixed farming systems (Zhou et al., 2019).

Typical dual-purpose breeds:

- Slovak Spotted cattle – a typical dual-purpose breed suitable for both milk and meat production.
- Simmental (Fleckvieh) – a classic dual-purpose breed widely distributed in Europe.
- Brown Swiss – primarily a dairy breed, but some lines are also suitable for meat production (partially dual-purpose).
- Montbéliarde – a French dual-purpose breed suitable for both milk and meat.
- Normande – a French dual-purpose breed known for high-quality milk and meat (Baldini et al., 2020).

Dual-purpose programmes are primarily used to increase farm economic stability, as they allow income generation not only from milk production but also from meat sales. An important benefit is the better utilisation of bull calves and culled cows, which achieve more favourable growth and carcass traits compared with highly specialised dairy breeds. These systems are particularly suitable for areas with less favourable production conditions, where it is not possible to ensure the high intensity of nutrition and management typical of intensive dairy farms. Under such conditions, dual-purpose breeds show better adaptability, higher resilience, and more stable production (Baldini et al., 2020).

From the perspective of modern livestock production, dual-purpose programmes also play an important role in animal welfare and production sustainability. They are associated with longer productive lifespans, lower incidence of health disorders, and more efficient use of input resources, contributing to reduced environmental burden and higher societal acceptance of cattle farming (Krupová et al., 2016).

2.2.2 Breeds and Their Productivity

Among the most important dairy breeds used in both intensive and extensive production systems worldwide are:

- Holstein-Friesian – the most widespread and most productive dairy breed in the world.
- Brown Swiss – a breed with high milk production and good milk component quality.
- Jersey – smaller animals with high fat and protein content in milk.
- Guernsey – a breed producing "golden" milk with higher beta-carotene and fat content.
- Ayrshire – a robust breed suitable for pasture-based systems.

Holstein-Friesian is considered the global standard breed in terms of milk productivity. Under commercial conditions, annual production can reach an average of 25,000–30,000 pounds (≈ 11,340–13,605 kg) of milk per cow per standard lactation, while record-producing cows may exceed 35,000 kg of milk per lactation. According to Agri-Stat (FAO, 2022a), Holstein is present in more than 150 countries, making it the most widespread dairy breed globally. Milk contains an average of 3.7% fat and 3.2% protein.

Brown Swiss is a breed known for the combination of solid productivity and very good milk quality, especially with a high protein content suitable for cheese processing. Standard annual yield ranges from 10,500–11,800 kg of milk, with approximately 4% fat and 3.5% protein. The breed is considered robust and well adapted to various climatic conditions, which contributes to its widespread use outside Central Europe (Wirth et al., 2021).

Jersey is characterised by high fat and protein content in milk, which makes it suitable for butter and cheese production. Although milk yield is lower than in Holstein (≈ 7,500–8,500 kg annually), milk is rich in solids with about 5% fat and 4.0% protein, increasing its value for processing (Goni et al., 2015).

Table 4 Comparison of major breeds by productivity and milk quality

Breed	Annual yield (kg)	Fat content (%)	Protein content (%)	Main use
Holstein-Friesian	11,340–13,605	3.7	3.2	Milk quantity
Brown Swiss	10,500–11,800	4.0	3.5	Cheese, multipurpose
Jersey	7,500–8,500	5.0	4.0	Butter, cheese, high-quality milk

Source: Goni et al., 2015; Wirth et al., 2021

Other important dairy breeds include Guernsey and Ayrshire, which are characterised by either higher milk fat content (Guernsey) or a balanced combination of quality and production (Ayrshire). Annual milk production in these breeds ranges from approximately 10,000–15,000 kg, depending on management, nutrition, and genetic potential of the herd (Mullan et al., 2022).

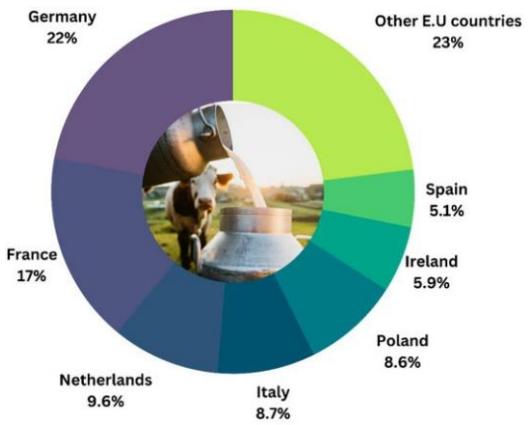


Figure 3 Share of individual EU Member States (excluding Luxembourg) in total milk production in 2020.

Source: Eurostat, 2021

2.2.3 Factors Affecting Dairy Cow Milk Yield

Milk yield in dairy cows is the result of a complex interaction of multiple biological, technological, and environmental factors (Hocquette and Chatellier, 2011; Monteiro et al., 2013). Although the genetic potential of a breed forms the basic prerequisite for high milk production, it does not by itself guarantee optimal results. Without adequate nutrition, health care, environment, and proper herd management, the genetic potential of animals often remains underutilised (European Commission, 2003; Lengyel et al., 2003).

Genetic factors determine the upper limit of milk yield, milk composition, and the animal's ability to respond to environmental conditions (Ngapo and Gariépy, 2006; Sakowski et al., 2022). Breeding programmes focused on production and functional traits such as longevity, disease resistance, and reproductive performance play a key role in the long-term efficiency of dairy farming (Hocquette and Chatellier, 2011; Kostusiak et al., 2023). However, even genetically superior animals require optimal conditions in order to fully realise this potential (Park et al., 2018).

Nutrition is one of the most important factors affecting milk production (Monteiro et al., 2013; Revilla and Vivar-Quintana, 2006). An energy- and nutrient-balanced ration must correspond to the cow's production stage, body condition, and health status (MLA, 2017). Adequate intake of energy, protein, minerals, and vitamins is essential not only for high milk production but also for maintaining good reproductive performance and preventing metabolic disorders such as ketosis and ruminal acidosis (Pardon et al., 2014). The quality of forage and appropriate feeding technology are therefore of fundamental importance (Lengyel et al., 2003).

Health management significantly influences the stability and sustainability of milk yield (Sakowski et al., 2022). Prevention of diseases, especially mastitis and metabolic and reproductive disorders, directly reduces production losses and farm operating costs (European Commission, 2003). Regular veterinary inspections, health monitoring, proper milking hygiene, and clean housing conditions are essential tools of effective herd health management (Hocquette and Chatellier, 2011). Healthy cows are able to utilise nutrients more efficiently and maintain higher milk production throughout lactation (Monteiro et al., 2013).

The environment and animal welfare are becoming increasingly important in modern dairy production systems (Ngapo and Gariépy, 2006; Tan and Jiang, 2024). Optimal barn microclimate, including suitable temperature, humidity, and air quality directly influence the physiological status of animals (Brown and Claxton, 2011). Heat stress can significantly reduce feed intake and consequently milk yield (Park et al., 2018). Adequate lying space, high-quality

bedding, and minimisation of stress factors contribute to improved health status and higher milk production (Tan and Jiang, 2024).

Ultimately, milk yield is the result of the synergistic interaction of all the factors mentioned above (Hocquette and Chatellier, 2011). Effective herd management must therefore consider the dairy cow as a biological system in which genetics, nutrition, health, and environment are interconnected (Monteiro et al., 2013). Only a comprehensive and systematic approach enables the achievement of high, economically efficient, and sustainable milk production while maintaining good animal welfare (European Commission, 2003).

According to FAO, cattle account for more than 80% of global milk production, with total milk production from all lactating species reaching approximately 930 million tonnes in 2022 (FAO, 2022).

Although the number of dairy farms is declining in developed countries, productivity per cow continues to increase due to genetic improvement and modern management practices (EUROSTAT, 2015; Sakowski et al., 2022). In developing regions, the opposite trend is observed – the number of dairy cows is increasing, but their average productivity remains lower, often due to less intensive nutrition and limited access to technological innovations (FAO, 2022a; Papanikolopoulou et al., 2025).

Dairy cattle breeding forms the foundation of the modern dairy industry (Ngapo and Gariépy, 2006). Major breeds such as Holstein-Friesian, Brown Swiss, and Jersey provide different combinations of milk yield and milk quality adapted to market demands (Monteiro et al., 2013). However, the success of dairy farming depends not only on breed, but also on an integrated approach including nutrition, health care, environment, and genetic selection is essential for achieving the full utilisation of production potential (Hocquette and Chatellier, 2011).

2.2.4 Benefits of Milk and Dairy Product Consumption for Human Health

The most significant benefit of milk and dairy products is their positive impact on human health. Through milk and certain dairy products, people of all age groups (from childhood to old age) can support the proper functioning of the body and positively influence digestion, metabolism, and blood pressure. Fermented and probiotic products are particularly important, as they represent a valuable source of biologically active compounds and should be part of a regular diet (Zhang et al., 2021).

Milk is an important source of energy due to its fat and carbohydrate content and also provides high-quality protein rich in essential amino acids. It contains all major minerals, including calcium, phosphorus, magnesium, sodium, potassium, sulphur, and chlorine. One litre of milk contains approximately 1,200 mg of calcium, which can cover the daily requirement for this mineral. In addition, it provides several trace elements such as copper, fluoride, iodine, manganese, zinc, molybdenum, and selenium (Akyil Ali et al., 2025).

Milk also provides all 13 vitamins required by the human body. It contains carotenoids as precursors of vitamin A, vitamin E, and significant amounts of B vitamins. It is particularly rich in riboflavin (vitamin B_2), which plays an important role in nutrient metabolism, the formation of red blood cells and antibodies, and the maintenance of healthy vision, skin, hair, and nails. It also contributes to reducing fatigue and improving overall health. Therefore, milk and dairy products represent an important source of biologically active substances essential for healthy growth, development, and proper body function (Akyil et al., 2025).

Milk is therefore an important food not only for children but also for adults. It is characterised by a favourable ratio and sufficient amount of essential nutrients. The proteins contained in one litre of milk can cover up to half of the daily protein requirement; the same amount provides approximately 20% of daily energy needs, one quarter of the requirement for vitamins A and B, about one sixth of the daily requirement for vitamin C, approximately 70% of the daily requirement for phosphorus, and the full daily requirement for calcium (Akyil et al., 2025).

From a long-term perspective, however, it is unfavourable that recent decades have seen a significant decline in livestock production, the food industry, and the dairy sector. Despite favourable natural conditions, land use per capita remains low and milk and meat production is insufficient, which negatively affects public health. Consumption of dairy products is among the lowest in the European Union, and an increasing share of food (including dairy products, meat, fruit, and vegetables) is imported. The lack of a long-term development strategy has led to a gradual loss of food self-sufficiency, which has a particularly negative impact on rural areas and their overall prosperity. Rural areas without agriculture lose their essence (Kubicová et al., 2021).

Despite the decline in cow's milk production, cheese consumption is not decreasing; on the contrary, it is slightly increasing due to imports. This increase is mainly driven by the development of specialty cheeses, including products made from sheep's milk, which contribute to higher consumption of dairy products. The production of natural cheeses in

Slovakia has stabilised, and the production of speciality cheeses in small artisanal dairies is becoming increasingly important (Kubicová et al., 2021).

2.3 Management of Dairy and Beef Cattle on Production Farms

Cattle herd management on production farms is a complex process that includes animal health management, optimisation of nutrition, efficient housing, and the implementation of modern technologies aimed at increasing milk and meat production, ensuring animal welfare, and minimising costs and health problems (Kováč et al., 2023).

A key aspect is ensuring optimal housing conditions that influence production, welfare, and animal health. Proper housing improves comfort, reduces stress, and minimises the risk of infections. In dairy cows, the focus is on maximising milk production, whereas in young or beef cattle the priority is optimal conditions for growth, improved feed conversion, and muscle quality. Comfortable housing emphasises:

• **Rest and movement space** – lying areas must be clean, dry, and comfortable to reduce lameness and increase blood supply to the udder in dairy cows (by 50% when lying more than 10 hours per day).

• **Flooring** – concrete is durable and easy to clean but may increase susceptibility to lameness; grooved floors or rubber mats are recommended to reduce hardness and slipperiness (De Vries, 2013).

• **Automated feeding and watering systems**, enabling precise feed and water delivery for all animal categories.

Over the last two decades, many farms have shifted to loose housing systems that allow animals greater freedom of movement, improve welfare, and support muscle growth in beef cattle as well as higher milk production in dairy cows. Animals are housed in group pens or cubicle systems, and various bedding materials are used such as, straw, sawdust, sand, or geotextile mattresses. Nutrition and feeding management are key for both production sectors:

- For dairy cows, TMR is optimised to support high lactation and prevent metabolic diseases such as acidosis, ketosis, and milk fever.
- For beef cattle, the goal is to achieve maximum feed conversion, support healthy muscle growth, and minimise undesirable fat infiltration that reduces meat quality (Sordillo et al., 2009).

Proper management also includes control of the reproductive cycle and grouping animals according to stage of lactation, calving period, or age. Housing capacity must be adapted to the number of pregnant heifers, dry cows, and production cows (Kováč et al., 2016).

Health care is critical for maintaining high performance:

- In dairy cows, monitoring focuses on mastitis, lameness, metritis, laminitis, and metabolic disorders.
- In beef cattle, monitoring focuses on healthy growth, infection prevention, and optimal body condition before slaughter (Sordillo et al., 2009).

Table 5 Reproductive cycle

Period	Duration (days)	Share (%)	Number of cows (100 herd)
Production period	335	83.7	84
Dry period	51	12.8	13
Maternity pen	14	3.5	3

Source: Kováč et al., 2016

This distribution of the reproductive cycle is typical for intensive dairy systems; however, the basic principles of reproductive management are also applicable to beef cattle production.

The aim of management is to ensure a regular annual calving interval, optimal body condition of cows, and sufficient calf growth, which directly affects farm economics. Differences between dairy and beef breeds are reflected mainly in nutritional requirements, management intensity, and production evaluation, rather than in the basic structure of the reproductive cycle (NRC, 2001; Kováč et al., 2016).

Effective management must integrate milk production, environmental optimisation, nutrition, and animal health care to maximise economic efficiency while ensuring cattle welfare (Sordillo et al., 2009).

If pregnant heifers are housed together with dry cows, sufficient housing capacity must be ensured. For a herd of 100 cows, with 30% culling and pregnant heifers housed with cows approximately two months before calving, at least 105 housing spaces are required (Sordillo et al., 2009).

Production cows may be further divided into smaller groups according to stage of reproduction or production level. Such grouping allows targeted feeding, better work organisation, and reduced animal stress. During group feeding, cows should be grouped so that production differences within the group are minimal, preventing overfeeding of low-producing cows and production decline in high-producing individuals. During calving, cows are housed in separate facilities used for pre-calving preparation, calving, and post-calving adaptation before joining the production group. Proper management of this period is essential for both dairy and beef cattle, as it directly affects calf viability, cow body condition, and regularity of the reproductive cycle. The capacity of maternity facilities must also consider seasonal or concentrated calving (Sordillo et al., 2009).

Animal health is a key component of cattle management. Intensification of milk and meat production has increased productivity but also the incidence of metabolic, reproductive, and infectious diseases, especially during the transition period and early lactation. These diseases represent a significant source of economic loss and are closely linked to nutrition, management, and animal welfare (Sordillo et al., 2009).

Management of beef cattle herds focuses primarily on efficient meat production while ensuring good health, welfare, and economic sustainability. Unlike dairy farms, the main goal is to achieve high daily weight gain, optimal feed conversion, and desired carcass quality in the shortest possible time. Successful management requires coordination of nutrition, reproduction, disease prevention, housing, and systematic monitoring of production indicators (Owens et al., 1995; Lawrence et al., 2012).

Nutrition is a key factor influencing growth, muscle development, and metabolic stability. High-energy diets with a high proportion of concentrates are commonly used in beef finishing systems. Adequate structural fibre must be ensured to maintain rumen fermentation and prevent metabolic disorders, especially subacute ruminal acidosis. Proper transitions between diets and monitoring feed intake are essential (Owens et al., 1998; Galyean and Hubbert, 2014).

Reproductive management in beef cattle herds is oriented towards maximising the genetic potential of the herd, particularly in terms of growth performance, feed conversion, and meat quality. The selection of breeding animals is based on production indicators and the use of genetic evaluations. Artificial insemination enables the rapid dissemination of desirable genetic traits and increases production uniformity within the herd (Diskin and Kenny, 2014).

Nutritional management of cows during the pre- and post-calving period has a crucial impact on reproductive performance, calf vitality, and the long-term production efficiency of the herd (Constable et al., 2016).

Health care is an integral part of management, particularly in intensive finishing systems where the risk of infectious and metabolic diseases is higher. Preventive programmes include regular vaccination, control of internal and external parasites, and systematic monitoring of animal health status (Constable et al., 2016). Early identification of behavioural changes or reduced feed intake allows rapid intervention and minimisation of economic losses (MSD Veterinary Manual, 2023).

Even in intensive production systems, appropriate housing conditions must be ensured with an emphasis on animal welfare. Adequate space, good ventilation, dry lying areas, and measures to reduce heat stress have a significant impact on health status, growth, and the overall well-being of cattle. Increasing societal and legislative emphasis on welfare is also shaping modern production systems (Grandin, 2020).

Modern management of beef cattle herds increasingly relies on digital technologies and data-driven decision-making. Monitoring daily weight gain, feed intake, feed conversion ratio (FCR), and health indicators enables optimisation of finishing strategies and improvement of economic efficiency (Lawrence et al., 2012). At the same time, the importance of production sustainability is increasing, particularly in reducing environmental impact through efficient nutrition, herd management, and optimisation of production processes (FAO, 2019).

Maintaining good animal health is a crucial aspect of cattle management. Intensification of milk and meat production is associated with increased demands on metabolism, the immune system, and adaptive capacity, which may lead to a higher incidence of health disorders. Cattle diseases negatively affect production parameters, reproductive performance, calf viability, and ultimately the economics of the farm.

Health problems occur most frequently around the time of calving and in the early production stage, when animals are exposed to significant metabolic and physiological stress. In dairy cows, these disorders are manifested mainly by decreased milk yield and reduced milk quality, while in beef breeds they lead to reduced growth performance, poorer body condition, and prolonged reproductive intervals.

Effective prevention of health disorders is based on a comprehensive approach that includes optimal nutrition, appropriate housing, stress minimisation, and systematic monitoring of animal health. Such an approach contributes to stable production, reduced need for treatment, and the assurance of a high level of cattle welfare (Sordillo et al., 2009).

3 Health Status of Cattle and Its Impact on the Safety of Products in the Primary Production of Meat and Milk

3.1 Beef Cattle Production and Meat Production

The safety of beef in primary production in the case of beef breeds is based on a simple, but often underestimated fact: the key bacterial risks for consumers largely arise before slaughter, either as silent (subclinical) carriage of zoonotic bacteria in the gastrointestinal tract and on the skin, or as a consequence of diseases that worsen the hygienic status of the animal (diarrhoea, soiling of the coat, injuries) and increase the likelihood of carcass contamination during hide removal and evisceration. In beef production systems (cow-calf, weaning, transfer to finishing, transport and lairage), stress events accumulate, which may alter pathogen shedding and promote spread within the group. EU surveillance also shows that among the most frequently reported zoonoses in humans are salmonellosis, campylobacteriosis and infections caused by Shiga toxin-producing *Escherichia* (*E.*) *coli* (STEC), while STEC and salmonellosis are directly relevant to the beef chain and raw beef; listeriosis is less common but the most severe in terms of hospitalisation and mortality of human (EFSA and ECDC, 2025b).

From a bacteriological perspective, morbidity in beef breeds in the context of meat safety can be divided into two lines:

- **The first line** includes zoonotic bacteria that often do not cause clinical disease in cattle but are crucial for meat contamination and subsequent human illness.
- **The second line** includes bacterial diseases typical for production (especially respiratory diseases), which may not be classical foodborne infections but increase the need for treatment, alter animal health status and indirectly worsen hygiene conditions before slaughter. Since the next chapter addresses antimicrobial resistance, it is important here to highlight where bacterial morbidity intersects with primary production safety and why prevention of bacterial problems is simultaneously prevention of food risks (Flach et al., 2023; Bakin et al., 2025).

The most important zoonotic group in primary beef production remains **Shiga toxin-producing *E. coli* (STEC)**. Cattle are a natural reservoir of STEC and can shed these bacteria for prolonged periods without clinical signs. From the perspective of primary production, the critical point is that the “risk” is not only the presence in the intestine, but especially the transfer to hides and to the environment, where bacteria persist and circulate among animals. Recent

studies emphasise the need for pre-harvest approaches aimed at reducing faecal shedding and hide contamination before animals arrive at the slaughterhouse, because hides represent one of the main sources of carcass surface contamination during dehiding (Flach et al., 2023; Bakin et al., 2025). In this context, the international synthesis of evidence on interventions against STEC across the food chain (including on-farm and pre-slaughter interventions) published by FAO is of major importance (FAO 2022b). The latest reviews and analyses of pre-harvest interventions show that the tested approaches are highly heterogeneous (feed and water additives, immunisation, management interventions), and the outcomes vary according to study design and production conditions. The practical implication is that a single intervention is rarely sufficient, and effectiveness increases through a combination of hygiene, group management, stress reduction, and targeted prevention. In beef breeds, the most critical period for bacterial shedding dynamics is often weaning followed by transfer to feedlots, where animal mixing and dietary changes promote the spread of enteric bacteria (Bakin et al., 2025).

The second key zoonotic concern is ***Salmonella enterica*** **serovars Dublin, Typhimurium, and Newport**. Unlike STEC, which is primarily associated with surface contamination and hygienic barriers, *Salmonella* spp. in cattle presents a major challenge due to peripheral lymph nodes. Current studies repeatedly show that *Salmonella* spp. can persist in the peripheral lymph nodes of slaughter cattle, which are "protected" from surface decontamination procedures at slaughterhouses; if lymph nodes enter raw material (especially during ground beef production), a contamination pathway arises that cannot be controlled solely by improving carcass surface hygiene. This mechanism is discussed in detail by Wottlin et al. (2022) and supported by longitudinal data on the occurrence and characterisation of salmonela in lymph nodes and beef trim in processing plants (Nickodem et al., 2023; Delgado-Suárez et al., 2024). From the primary production perspective, this means that salmonela cannot be viewed only as a slaughterhouse issue; it must include reduction of infection pressure and exposure on farms and in feedlots (feed, water, biosecurity, pest control, manure management, isolation of clinical cases), because these stages determine whether *Salmonella* spp. becomes established in the population and gains the opportunity to invade tissues and lymph nodes. A recent review by Imanuela et al. (2024) summarises the routes of introduction and persistence of Salmonella in cattle herds and emphasises that once introduced, it can become an endemic problem if biosecurity and hygiene are not adequately implemented.

Listeria monocytogenes in primary beef production has traditionally been associated more with feed and the environment than with clinical disease in beef breeds; however, it is relevant to meat safety because it can persist in the environment and be transmitted through

contaminated surfaces, bedding, water, and animal handling. A recent literature synthesis specifically focused on beef highlights that *L. monocytogenes* in beef is often "less in the spotlight" compared with *Salmonella* spp. and *E. coli*, although non-negligible prevalence in beef and beef products has been demonstrated in several countries and typical contamination routes have been described. In beef production, the practical importance lies in strict management of animal cleanliness before transport, hygiene of drinkers, contact with silage or potentially contaminated feed, and reduction of stress and contamination during the pre-slaughter period, when the risk of bacterial transfer to hides and subsequently to carcasses increases significantly (Reis et al., 2024).

A specific category of bacterial risk is ***Mycobacterium bovis*** **(bovine tuberculosis)**. Although this is a chronic disease and prevalence in many EU regions is low, low prevalence increases the importance of surveillance. Recent assessments show that **post-mortem inspection at slaughterhouses** remains a key tool in low-prevalence areas for detecting residual cases and supporting tuberculosis-free status. In the context of primary beef production, the importance of *M. bovis* is twofold: it represents a zoonotic risk (especially where control is insufficient and in settings with close human-animal contact) and has economic and trade consequences for farms and animal movements. Therefore, beef herds must maintain strict record-keeping, traceability, and biosecurity during animal purchases and movements, and veterinary supervision should use slaughterhouse surveillance data as feedback for on-farm risk management (Gomez-Buendia et al., 2025).

In addition to zoonotic bacteria, the **bacterial component of the bovine respiratory disease complex (BRD)** is particularly important in beef cattle. BRD is typically triggered by a combination of stress and viral infections, but the clinical manifestation of pneumonia and the most severe losses are often associated with bacterial pathogens that are present in the upper respiratory tract as commensals and, when the immune system is weakened, become opportunistic pathogens. The most frequently reported agents include *Mannheimia haemolytica, Pasteurella multocida, Histophilus somni,* and *Mycoplasma bovis* (O'Donoghue et al., 2025; Storoni, 2025). Although BRD is not primarily a foodborne disease, its relationship to safety in primary production is practical. Diseased animals have poorer welfare and often require therapy, while the likelihood of contamination between groups during handling and stress increases, worsening hygiene and potentially contributing to greater contamination of hides and the environment with pathogens. In beef production systems, this is typically associated with the post-weaning and post-transport periods, when respiratory stress coincides with psychological stress and reduced animal cleanliness. Consequently, prevention of BRD

(housing, ventilation, minimising mixing, weaning and transport management, risk-based vaccination) is also a preventive step for hygiene and safety in the pre-slaughter stage of meat production (Deng et al., 2017; Da Costa Freitas and Barbosa, 2025).

The key bridge between **animal health** and **meat safety** in primary production is therefore the level of animal contamination before slaughter, particularly of hides and limbs, and the degree of faecal contamination. Modern operational studies show that hide contamination can increase during housing and animal movements, confirming the importance of interventions before entry into slaughterhouses (Flach et al., 2023). In primary production, this means that herd health and hygiene management must target periods when animals are "prepared" for slaughter: selection and removal of clinically ill animals, minimisation of contamination, appropriate bedding and watering management, and reduction of stress before transport. For STEC and *Salmonella* spp., it is also essential to understand that risk is dynamic and group-based rather than individual: animal mixing, dietary changes, and environmental pressure can cause rapid changes in shedding prevalence and consequently in hide and environmental contamination (EFSA and ECDC, 2025a; FAO 2022b; Nickodem et al., 2023).

From a public health perspective, these mechanisms are reflected in European **One Health reports**, which integrate surveillance data from humans, animals, and food. The most recent report (2024) summarises trends in major zoonoses in the EU and provides a framework for prioritising risks in the food chain, including salmonellosis and STEC infections (EFSA and ECDC, 2025b; ECDC, 2025b). For beef production, this implies a practical requirement: management of bacterial risks in beef herds must be based on a combination of biosecurity, environmental hygiene, stress management, and targeted prevention during critical periods (weaning, movements, finishing, pre-slaughter preparation). Proper implementation reduces not only clinical disease but also the likelihood that zoonotic bacteria move from the intestine and environment to hides and subsequently contaminate meat (EFSA and ECDC, 2025b; Bakin et al., 2025). It is important to emphasise that bacterial disease in beef cattle and meat safety in primary production share a common denominator in prevention and herd organisation. Reducing the incidence of BRD and enteric problems decreases the number of "high-risk" animals with poorer hygiene status, lower body condition, and increased need for therapeutic interventions, which in turn reduces hide contamination and the risk of microbial transfer during slaughter (FAO and WHO, 2022; EFSA and ECDC, 2025b). Reducing the prevalence of *Salmonella* spp. in herds may lead to a lower risk of colonisation of peripheral lymph nodes, which are considered a significant source of contamination of ground beef and represent a specific challenge for the safety of this commodity (Wottlin et al., 2022; Delgado-Suárez et al.,

2024). These issues are closely linked to the emergence and spread of antimicrobial resistance, since the intensity and nature of bacterial diseases in herds largely determine the extent and type of antimicrobial use and the resulting selection pressure supporting resistant bacterial populations (FAO and WHO, 2022; EFSA, 2023).

Therefore, in meat production it is essential to ensure food hygiene and safety already at the stage of primary production – from farming practices, feeding, housing, and animal health care to subsequent processing and transport stages.

Within the EU legal framework, the so-called **"Hygiene Package"** has been established, notably Regulation (EC) No. 852/2004 on the hygiene of foodstuffs and Regulation (EC) No. 853/2004 laying down specific hygiene rules for food of animal origin. These rules apply to all stages of production within the **"Farm to Fork"** strategy. Hygiene requirements include the implementation of systems such as HACCP (Hazard Analysis and Critical Control Points) or other codes of good hygiene practice, which enable the identification of critical points in the meat production chain and minimise the risk of contamination or pathogen spread (Tankosić et al., 2006).

These general hygiene requirements are complemented by Regulation (EC) No. 2073/2005 on microbiological criteria for foodstuffs, which establishes food safety criteria and process hygiene criteria and defines the responsibilities of food business operators in monitoring the occurrence of selected microorganisms during meat production and processing, including beef.

During processing, transport, slaughter, and cutting of meat, specific hygiene requirements must also be met regarding premises, equipment, cleaning and sanitation, labelling, traceability, and monitoring of animal health status, thereby ensuring risk control throughout the entire food chain (Kozačinski et al., 2016).

3.1.1 Disease Prevention Programs in Beef Cattle Herds

Disease prevention in beef cattle production is based on a systematic combination of managerial, nutritional, hygienic, and veterinary measures aimed at minimising disease occurrence, reducing the need for treatment, and ensuring stable animal growth. Since clinical disease in beef cattle often leads to reduced daily weight gains, poorer feed conversion, and increased mortality, a preventive approach is essential for the economic sustainability of production (Radostits et al., 2006).

One of the fundamental preventive steps is the careful management of stress factors, particularly during critical periods such as calf weaning, animal transport, group mixing, and adaptation to new diets. **Stress** is considered a major predisposing factor for the development of respiratory diseases in cattle, especially BRD. Practical measures include gradual weaning of calves, limiting the sudden mixing of unfamiliar animals, and ensuring appropriate microclimatic housing conditions, particularly adequate ventilation and a dry environment (Fulton, 2009; Taylor et al., 2010).

A key element in the prevention of infectious diseases is the implementation of a **targeted vaccination strategy**. In beef cattle herds, vaccination is primarily focused on respiratory viruses (IBR, BVD, PI3, BRSV), clostridial diseases, and in some systems also leptospirosis. Vaccination programs are designed so that immunisation occurs before animals are exposed to increased stress or infectious pressure, for example before weaning or transfer to the finishing phase. Proper timing of vaccination significantly reduces the incidence of clinical cases and subsequent production losses (Radostits et al., 2006; Uzal et al., 2019).

Prevention of parasitic diseases is also highly important, particularly in extensive and pasture-based production systems. Practical steps include regular monitoring of body condition and growth, strategic deworming based on risk periods, and pasture rotation. Parasitic infections often occur subclinically but lead to poorer feed conversion and slower growth, resulting in significant economic losses (Sutherland and Leathwick, 2011).

Prevention of metabolic disorders in intensive finishing systems is closely linked to nutritional management. Practical measures include the gradual transition from forage-based diets to high-energy rations, ensuring sufficient structural fibre content, and regular monitoring of feed intake within animal groups. These steps are essential to prevent subacute ruminal acidosis, which can lead to reduced weight gain, laminitis, and increased lameness (Owens et al., 1998; Galyean and Hubbert, 2014).

Strict **biosecurity** is an integral part of disease prevention. In practice, this involves quarantine procedures for newly purchased animals, control of the movement of people and equipment on the farm, and regular hygiene of housing facilities. Even in relatively low-intensity production systems, the introduction of infectious agents can lead to long-term health problems within the herd (FAO, 2010).

Disease prevention in beef cattle herds also includes **reproductive and health measures** aimed at ensuring good body condition of cows before breeding and calving, maintaining hygiene in calving areas, and providing timely supervision during calving. Proper

management of this period has a major impact on calf viability, the incidence of postpartum complications, and the regularity of the reproductive cycle (Diskin and Kenny, 2014).

3.2 Breeding of Dairy Cattle and Milk Production

The breeding of dairy cattle plays a key role in meeting the growing demand for milk and dairy products, which is closely linked to global population growth and changes in dietary habits. According to long-term projections, the share of fresh dairy products in total milk consumption will continue to increase over the next decade, particularly in developing countries where the most significant growth in consumption is expected (OECD/ FAO, 2018).

The safety and quality of milk are directly influenced by dairy cow management, animal health, environmental hygiene, and milking management. For this reason, it is essential to apply a comprehensive herd management approach that ensures the production of safe milk while maintaining animal welfare and economic efficiency.

The dairy sector is one of the key branches of agriculture in the European Union. In 2020, approximately 145 million tonnes of cow's milk were produced in the EU. Although milk production takes place in all Member States, the seven largest producing countries accounted for approximately 77% of total production, representing around 119 million tonnes of raw milk annually (Neculai-Valeanu et al., 2022).

In the EU, hygiene standards for raw milk from cows and other animals are also defined by relevant legislation. According to Annex III, Section IX, Chapter I of Regulation (EC) No. 853/2004, the bacterial count and somatic cell count (SCC) in raw cow's milk must not exceed 100,000 CFU/ml and 400,000 SCC/ml, respectively. These values are measured in raw milk before processing and provide information about udder health. Hygienic requirements for animals in production herds prohibit the collection of milk from diseased animals. Failure to comply with these standards poses a serious risk to consumer health, as microbiologically contaminated raw milk may contain pathogenic microorganisms and transmit diseases to humans. The incidence of milk-borne diseases is higher among individuals who consume raw milk than among those who drink pasteurised milk (Pyz-Lukasik et al., 2015).

Direct milk sales are defined as the direct supply of milk from the producer to the final consumer. According to Regulations (EC) No. 852/2004 and 853/2004, the direct sale of milk in the European Union is regulated by national legislation of individual Member States (Pyz-Lukasik et al., 2015).

A high bacterial count indicates contamination of milk from various sources, most commonly due to inadequate cleaning and disinfection of milking equipment (Oliver et al., 2009). Contaminated animals, cows with mastitis, poor milking practices, and failure to rapidly cool milk to <4.4°C may also contribute to high total viable counts in raw milk (Oliver et al., 2009).

Healthy dairy cows are a fundamental prerequisite for the production of safe milk. Any disease can affect its hygienic quality. The most important conditions include:

- **mastitis** – causing increased somatic cell counts and microbial contamination,
- **metabolic disorders** – reducing immunity and increasing infection risk,
- **infectious diseases** (e.g., brucellosis, tuberculosis) – representing zoonotic risks.

Mastitis is the most common infectious disease in dairy cows, with global economic losses estimated at more than USD 40 billion annually (Xuelong et al., 2022). Udder health is crucial for sustainable milk production. Mastitis is more than a health issue; it affects milk quality, animal performance, and the use of antimicrobials on farms (Neculai-Valeanu et al., 2022). Diagnosis of subclinical mastitis as well as early detection of clinical mastitis, which causes visible changes in milk secretion, is a fundamental component of any program aimed at improving dairy herd health. This goal has enormous economic importance for farmers and producers, as high somatic cell counts and bacterial presence have a serious negative impact on milk production and quality (Ruegg et al., 2017).

The hygienic quality of milk is assessed by the total viable count (TVC), with Regulation (EC) No. 853/2004 setting a limit of ≤100,000 CFU·ml^{-1}. Udder health is closely associated with the somatic cell count (SCC); values above 400,000 cells·ml^{-1} indicate an increased occurrence of subclinical mastitis, whereas the physiological range for a healthy cow is below 100,000–200,000 cells·ml^{-1}.

According to the type of causative agent, mastitis is divided into four main forms: bacterial, mycotic (fungal or algal), mycoplasmal, and nocardial. Bacteria are the most common causative agents, and approximately 150 species have been isolated from infected bovine udder tissue (Shaheen et al., 2016). Based on cellular and molecular morphology, **bacterial pathogens** are divided into Gram-negative species such as *E. coli* and *Klebsiella pneumoniae*, and Gram-positive species such as *Streptococcus agalactiae*, *Streptococcus uberis*, and *Staphylococcus aureus* (Arruda et al., 2013).

Based on transmission route, mastitis is further classified as contagious or environmental (Alemu et al., 2013). Contagious mastitis spreads from an infected udder to a healthy animal (Smith and Hogan, 2001). Environmental mastitis results from contamination of the teat orifice by pathogens present in manure, mud, puddles, feed, or bedding (Smith and Hogan, 2008).

Typical contagious pathogens include *Staphylococcus aureus*, *Streptococcus agalactiae*, *Mycoplasma bovis*, and other mycoplasma species, whereas *Streptococcus uberis*, *Streptococcus dysgalactiae*, *E. coli*, and *Klebsiella* spp. are classified as environmental pathogens (Shaheen et al., 2016). Contagious pathogens often cause subclinical mastitis because they can survive on teat skin and in the teat canal. Environmental pathogens usually cause short-term infections (streptococcal infections lasting about 30 days and coliform infections about 10 days) and are more commonly associated with clinical mastitis. Therefore, they are less likely to spread persistently within the herd compared with the subclinical form (Smith and Hogan, 2008).

Mastitis may also have a **non-infectious origin**, for example due to traumatic injury of the mammary gland (Smith and Hogan, 2001). The udder possesses anatomical and immune defense mechanisms that prevent infection. One of the main protective barriers is the anatomical structure of the teat, which mechanically prevents pathogen entry into the teat canal. Pathogens may enter the teat canal within one to two hours after milking if the canal remains open. Bacterial fixation occurs through adhesion and colonisation of new tissues (Neijenhuis et al., 2001). Initially, bacteria damage tissues lining large milk ducts and cisterns and produce virulence factors that can damage milk-secreting cells. These damaged cells produce substances that attract leukocytes, causing leukocytes to migrate from blood into milk. These leukocytes can engulf and destroy bacteria, but if bacteria are not eliminated, they continue to multiply and affect smaller ducts and alveolar regions (Zhao and Lacasse, 2008).

Migration of leukocytes into milk represents one of the key defense reactions of the organism against mammary gland infection and leads to a significant increase in somatic cell count. This phenomenon has major diagnostic importance, as SCC is one of the most important indicators of udder health and serves as a reliable marker of mastitis.

The SCC is a key tool for assessing the severity of intramammary infection (IMI). As SCC is a natural component of milk, its analysis allows evaluation of milk quality, monitoring of herd health in relation to mastitis, and is also used as a criterion in milk payment systems. Somatic cells in milk consist of approximately 75% leukocytes (neutrophils, macrophages, and lymphocytes) and 25% epithelial cells.

The proportion of leukocytes varies depending on infection and other factors (Sharma et al., 2011). Erythrocytes may occur in concentrations from 0 to 1.51×10^6/ml. During inflammatory reactions, SCC increases sharply. Its value varies according to the presence and type of pathogen and virulence factors. SCC may also be influenced by age, stage of lactation, parity, milk production level, and environmental conditions (Nolan, 2017).

Among the available direct and indirect diagnostic methods for mastitis, rapid on-farm screening tests mainly include indirect techniques such as the California Mastitis Test (CMT), sodium lauryl sulphate test (SLST), Surf-Field Mastitis Test (SFMT), and White Side Test (WST) (Sharma et al., 2011). Despite its subjectivity, CMT is one of the most widely used mastitis tests worldwide. The test is based on a reagent containing detergent that causes coagulation of DNA in the nuclei of somatic cells. According to the visual intensity of gel formation, a CMT score is determined, from which the SCC value can be indirectly estimated (Whyte et al., 2005).

3.2.1 Mastitis Prevention Programme

Problems with milk quality on production farms are related to a high incidence of mastitis, a high somatic cell count (SCC), and high bacterial levels in tank milk. These issues reflect the level of hygiene and the health status of the mammary gland. The so-called subclinical mastitis is very dangerous, but essentially, problems with milk quality are most often the result of a combination of various factors and causes. The causes of issues in dairy cow husbandry are therefore complex, and identifying potential factors is very challenging (Hisira et al., 2023).

The decisive role in controlling the occurrence and spread of mastitis in the herd primarily lies in prevention. Prevention is based on strict adherence to procedures, protocols, and measures directly related to milk collection, which mainly include:

- clean and dry housing for dairy cows,
- properly chosen milking procedure,
- care of breastfeeding equipment - functional parameters, regular service,
- disinfection of teats after milking,
- use of antibiotics during cow insemination,
- early and proper (correct) treatment of clinical cases of mastitis,
- breaking down of chronically ill or incurable dairy cows.

Clean and dry housing for dairy cows: the breeding goal is to have clean, dry, and content dairy cows at the entrance to the milking parlour. The hygiene of the housing most often contributes to so-called environmental mastitis. The level of housing is especially important at the beginning and end of the dry period. It has been found that up to 65% of environmental clinical mastitis cases during lactation were caused by the same pathogen identified in cows during the dry period. From this perspective, the level of housing and the associated cleanliness of the teats deserve high priority in the management of high-producing dairy cows (Šubová et al., 2021).

The correct working procedure for milking: The working procedure in the milking parlour must meet all biological and hygienic requirements for the cow. It is important that the operator has a clearly written, well-defined working procedure that includes conditions specific to the farm, such as respecting the milking equipment's technical capabilities and maintaining udder cleanliness.

Care of milking equipment: The condition of the milking equipment is a key factor in the quality of milk, as well as the efficiency and effectiveness of milking. From this perspective, regular maintenance of the milking de equipment vice is essential. It is necessary to regularly monitor the lifespans of individual components of the milking equipment and to service and adjust the operational parameters of the milking technology. Underestimating and delaying regular inspections of the milking device in an attempt to 'save money' will later drain much more money from the company's funds.

Teat disinfection: It is very important to disinfect the teats as soon as possible after removing the milking unit. It is necessary to immerse two-thirds of the teat in the disinfectant solution. Disinfection after milking is the most effective way to reduce the risk of transmitting infectious mastitis from one cow to another. In some farms, teat disinfection before milking is also practiced, an effective measure to reduce the incidence of environmental mastitis (Ruegg, 2017).

Use of antibiotics when drying off cows: If a farm uses antibiotic treatment during cow drying-off, then this method must be followed for all dairy cows. Antibiotic drying-off is a suitable tool for eliminating mastitis caused by *Staphylococcus aureus*, especially those that did not respond to treatment during lactation. When administering antibiotics during drying-off, it is essential to follow proper hygiene procedures and principles of intramammary antibiotic application. When drying off cows, it is important to consider the hygiene of the housing environment. Early and appropriate (correct) treatment of clinical mastitis cases – emphasise to the staff in the milking parlor to detect and report suspicious cases promptly and responsibly.

After the disease is diagnosed, the cow should be separated and grouped with other sick cows, which must be milked last. It is necessary to identify the microbial pathogen and use only antibiotics to which it is sensitive (Zigo et al., 2021).

Culling chronically ill or incurable dairy cows: Culling is a very effective method of reducing bacterial pressure in the herd, especially in infections caused by *Staphylococcus aureus*. Culling is based on accurate records of mastitis frequency in individual cows, with repeated cases in the same cow and ineffective treatment as the primary reasons for removal from the herd (Holko et al., 2019).

Utilisation of AI in Mastitis Diagnosis: In recent years, substantial focus has been on developing artificial intelligence (AI) and machine learning (ML) tools for diagnosing mastitis. Traditional diagnostic methods are often slow, labour-intensive, and require specialised expertise. Implementing AI-powered diagnostic tools not only boosts veterinary efficiency but also helps prevent mastitis by enabling early-stage diagnosis (SM) with timely intervention. This leads to lower economic losses and reduces culling of dairy cows (Sarkar et al., 2023).

4 Antimicrobial Resistance

4.1. Antimicrobial Resistance in Production Agriculture

Antimicrobial resistance (AMR) represents one of the most complex threats to the stability of the global food chain. In this context, cattle play a key role, as they account for more than half of the global consumption of veterinary antibiotics, specifically 53.5%, corresponding to approximately 40,697 tonnes per year (Tiseo et al., 2020). This massive selective pressure accelerates the evolution of resistant bacterial genotypes that cross farm boundaries and enter ecosystems shared with humans. The development of resistance in cattle production is not an isolated biological phenomenon but the result of interactions between the drug, the host, and the environment. The fundamental mechanism is selective pressure, whereby antibiotic administration eliminates susceptible microbial populations and frees ecological niches for resistant strains.

Horizontal gene transfer (HGT) plays a key role, particularly within the intestinal microbiome of cattle. Through plasmids, bacteria such as *E. coli* or *Enterococcus* spp. exchange antimicrobial resistance genes (ARGs) not only among themselves but also with potentially pathogenic species (Zalewska et al., 2021). Current studies indicate that up to 77.5% of *E. coli* isolates on commercial farms show resistance to at least one type of antibiotic (MPRV SR, 2025).

At present, resistance among pathogens causing mastitis and respiratory diseases in cattle represents a critical issue. The highest resistance rates are consistently observed for β-lactam antibiotics, with treatment failure of amoxicillin in staphylococcal infections reaching up to 87.4%. In contrast, due to strict regulation within Europe, relatively high susceptibility to aminoglycosides such as gentamicin has been maintained (MPRV SR, 2025).

Microbiological analyses of milk samples in the study by Tvarožková et al. (2023) demonstrated that the most frequent mastitis pathogens in Slovakia are coagulase-negative staphylococci, *Staphylococcus aureus*, *E. coli*, *Streptococcus agalactiae*, and *Streptococcus uberis*. Implementation of targeted mastitis control measures in the monitored herds led to a decrease in contagious pathogens – *Staphylococcus aureus* from 11.75% (2017) to 9.01% (2022) and *Streptococcus agalactiae* from 10.03% to 1.86%. At the same time, a decrease in *Streptococcus uberis* was recorded from 19.77% to 13.66%. Conversely, an increase in environmental pathogens, particularly coagulase-negative staphylococci (24.07% → 38.20%) and *E. coli* (22.64% → 24.22%), points to deficiencies in housing hygiene and milking management. From an antimicrobial resistance perspective, high resistance rates of mastitis pathogens to commonly used antibiotics were observed. Coagulase-negative staphylococci and *Staphylococcus aureus* showed extremely high resistance to streptomycin (up to 96.8–100%), with increased resistance also recorded for neomycin, tetracycline, β-lactam antibiotics, and fluoroquinolones. *Streptococcus uberis* and *Streptococcus agalactiae* locally reached up to 100% resistance to aminoglycosides. These results clearly confirm that empirical mastitis treatment without pathogen identification and antimicrobial susceptibility testing significantly contributes to the selection of resistant strains (Tvarožková et al., 2023).

In beef cattle production, AMR is also a significant problem closely linked to animal health, production intensity, and antimicrobial use. In cow-calf systems and feedlots, antimicrobials are most commonly used in relation to BRD and enteric infections, which are among the main causes of calf morbidity and mortality. These diseases create selective pressure that promotes the emergence and persistence of resistant bacterial populations in herds and their environment (Doster et al., 2022; EFSA, 2023).

The use of metagenomic approaches has enabled detailed analysis of the resistome in beef cattle. Abi Younes et al. (2025) demonstrated the presence of a wide spectrum of antimicrobial resistance genes in the respiratory tract of feedlot calves with BRD. Genes conferring resistance to tetracyclines, macrolides, and β-lactam antibiotics were most frequently identified, with higher occurrence in animals treated with antimicrobials during the fattening period. The authors highlight that the respiratory tract can serve as an important

reservoir of resistance genes that persist even after clinical recovery and can further spread within the population (Abi Younes et al., 2025).

The importance of the intestinal microbiota as a reservoir of AMR is also documented by Doster et al. (2022), who investigated the effect of antimicrobial use on the faecal microbiota of cattle. Exposure to antimicrobials led to statistically significant changes in resistome composition, and the increase in resistance genes persisted after treatment cessation. Although antimicrobial exposure explained only a small portion of resistome variability (less than 1%), differences among animal groups, sampling times, and production conditions highlight the complex multifactorial nature of AMR spread in beef production systems (Doster et al., 2022).

Specific data on phenotypic resistance are provided by Ali et al. (2025), who analysed faecal *E. coli* isolates from cow-calf operations. Resistance to tetracyclines was observed in approximately 45–60% of isolates, while resistance to ampicillin ranged from 20–35% and resistance to sulphonamides reached approximately 30–40%. The presence of multidrug-resistant strains was also recorded, confirming that commensal *E. coli* represents an important indicator of selective pressure and a potential reservoir of resistance genes in beef production systems (Ali et al., 2025).

The role of production systems in AMR dissemination is further confirmed by Feng et al. (2025), who compared the faecal resistome of cattle from intensive feedlot systems (grain-fed) and extensive systems (grass-fed). A higher diversity of antimicrobial resistance genes was observed in animals from intensive systems, associated with higher infection pressure and greater antimicrobial use. However, resistance genes were also detected in animals without recent antimicrobial exposure, suggesting environmental persistence and circulation of AMR within production systems (Feng et al., 2025).

These findings confirm that antimicrobial resistance in beef cattle is not merely the result of individual treatment but the outcome of long-term production, health, and environmental factors. Implementation of diagnostic and therapeutic algorithms based on rational antibiotic use is therefore an essential tool in combating AMR in primary milk production in line with the One Health concept (Tvarožková et al., 2023).

An important indicator is the difference between farm management types. Data confirm that conventional farms show an average AMR prevalence of 14.5%, whereas organic farms, which use antibiotics only in necessary therapeutic cases, maintain this level below 9% (Zalewska et al., 2021).

Slaughterhouses also play an important role in meat production, as bacterial populations from different farms accumulate there, accelerating horizontal gene transfer among zoonotic

pathogens. This process is supported by the high density of microbial communities in pre-slaughter holding areas (EFSA and ECDC, 2025b). Slaughterhouses have been identified as risk reservoirs of resistant strains, particularly extraintestinal pathogenic *E. coli* (ExPEC). During hide removal and evisceration, resistant bacteria are transferred from the body surface or intestinal content to carcasses (fresh meat), where up to 52.3% of slaughterhouse environmental samples contained isolates resistant to key antimicrobials. Slaughterhouse wastewater also shows high concentrations of resistance genes (e.g., tet(A)), which can contaminate water bodies via drainage systems (Chowdhury et al., 2025).

The development of AMR on farms and in slaughterhouses is closely linked to waste management. It is estimated that 70–90% of administered antibiotics leave the animal's body in metabolically active form through excreta. Manure therefore becomes an important reservoir of ARGs. When subsequently applied as fertiliser, vertical dissemination of resistance into soil layers and groundwater occurs, representing a direct risk of contamination of plant production intended for human consumption (Zalewska et al., 2021).

4.2. Molecular and Environmental Mechanisms of AMR Transmission

4.2.1 Molecular and Environmental Mechanisms of AMR Transmission on Farms

On cattle farms, the primary driver of the emergence and spread of antimicrobial resistance is selective pressure generated not only by the use of therapeutic antimicrobials but also by environmental stressors. Current research highlights the key role of class 1 integrons in microbial populations of livestock. These mobile genetic elements enable bacteria to capture, integrate, and express antimicrobial resistance gene cassettes. Experimental studies have demonstrated that antibiotic treatment can rapidly alter the diversity of the resistome in the intestinal microbiome of cattle, documenting the rapid adaptation of bacterial populations to selective pressure (Gillings, 2014; Haley and Van Kessel et al., 2022).

Co-selection mediated by feed additives and environmental factors, particularly the presence of heavy metals in the farming environment, also plays a significant role in maintaining multidrug resistance. Several studies have shown that genes conferring resistance to metals, such as zinc (e.g., the *czc* operon) and copper (e.g., the *pco* operon), are often physically located on the same mobile genetic elements as genes encoding resistance to clinically important antimicrobials, including β-lactams, macrolides, carbapenems, and colistin (mcr-1). This co-localisation enables the simultaneous selection of multiple resistance traits, as selective pressure exerted by metals can promote the survival and spread of multidrug-resistant

bacteria even in the absence of antibiotic therapy (Seiler & Berendonk, 2012; Wales and Davies, 2015; Pal et al., 2015; Sun et al., 2017).

Metagenomic studies highlight the importance of bacteriophages as vectors of antimicrobial resistance genes in farm environments. Bacteriophages present in manure can transfer functional resistance genes, such as *bla*TEM and *tet*M, and contribute to horizontal resistance transfer even under conditions where bacterial conjugation is limited (Colavecchio et al., 2017; Calero-Cáceres et al., 2019; Ku et al., 2025).

In dairy herds, the spread of antimicrobial resistance is strongly associated with milk as a biological matrix that represents not only the final product but also a medium enabling the circulation of resistant bacteria within the herd. Resistant mastitis pathogens, particularly *Staphylococcus aureus*, coagulase-negative staphylococci, and *E. coli*, are shed into milk during active infection and may subsequently be transmitted between cows via milking equipment, handlers' hands, or reusable towels. A major mechanism of persistence of these bacteria is their ability to form biofilms on milking equipment surfaces, which enhances their survival and reduces the effectiveness of routine sanitation procedures, leading to repeated contamination of milk with resistant strains (Medina et al., 2025; Touaitia et al., 2025).

Inadequate or inappropriate mastitis therapy represents another key factor promoting the selection and spread of resistance. Empirical treatment without prior culture and antimicrobial susceptibility testing, incorrect treatment duration, or repeated intramammary applications may expose bacteria to sub-inhibitory concentrations of antimicrobials. Such conditions promote the survival of tolerant bacterial subpopulations, increase biofilm formation, and create a favourable environment for horizontal transfer of resistance genes among bacteria in the milk microenvironment, particularly via mobile genetic elements such as plasmids and transposons (Kazemzadeh et al., 2025).

The impact of therapeutic interventions on antimicrobial resistance development is also documented by longitudinal studies focusing on dry cow therapy. Okello et al. (2023) demonstrated that following intramammary antimicrobial administration at drying off, some mastitis pathogens, particularly coagulase-negative staphylococci, showed increased resistance after calving, including resistance to tetracyclines. Although the overall resistance levels of major pathogens remained relatively low, the results highlight the importance of selective pressure generated by blanket therapy without a targeted approach. In line with this, Ruegg (2025) emphasises the need for antimicrobial stewardship in dairy herds based on selective treatment protocols, culture-guided decision-making, and rigorous mastitis prevention as key

tools for limiting the spread of antimicrobial resistance via milk (Okello et al., 2023; Ruegg, 2025).

4.2.2 Molecular and Environmental Mechanisms of AMR Transmission during Slaughter and Carcass Processing

Similarly, in slaughterhouses, the fundamental mechanism of antimicrobial resistance dissemination is HGT. This process is significantly accelerated by animal stress during transport and pre-slaughter handling, which leads to increased intestinal permeability, altered gut microbiome dynamics, and increased shedding of resistant bacteria into the environment. The most important HGT mechanism in slaughterhouse conditions is conjugation, during which direct contact occurs between bacterial cells via sex pili. Plasmids carrying resistance genes, such as *bla*CTX-M encoding resistance to cephalosporins, can rapidly spread between the indicator *E. coli* and pathogens such as *Salmonella* spp. (Mulchandani et al., 2023). Integrons and transposons also play an important role by enabling the integration of multiple resistance cassettes into the bacterial chromosome. This mechanism explains the high level of multidrug resistance recorded in 2024 in 43.8% of analysed isolates originating from cattle and slaughterhouse environments (EFSA and ECDC, 2025a).

Slaughterhouses represent environments with high humidity and substantial organic load, which significantly facilitates the transfer of bacteria from primary reservoirs to the final product. During evisceration, microscopic leakage of intestinal content may occur that is not always visually detectable. Metagenomic analyses have confirmed that the concentration of antimicrobial resistance genes in the bovine caecum can be up to three logarithmic orders higher than on carcass surfaces prior to processing, highlighting the high contamination potential during technological operations. Mechanical processes such as hide removal, animal handling, and high-pressure cleaning generate bioaerosols in slaughterhouse environments. These aerosols can contain viable bacteria, including antimicrobial-resistant strains such as methicillin-resistant *Staphylococcus aureus* (MRSA), which has been detected in slaughterhouse environments and among workers (Ivbule et al., 2017). Bioaerosols originating from animal production and processing systems are known to contain viable microorganisms, antibiotic-resistant bacteria, and antibiotic resistance genes (ARGs), which may be transported through the air and deposited on surrounding surfaces (McEachran et al., 2015). Importantly, airborne particles can also carry extracellular DNA (eDNA) containing resistance genes, which

may persist in the environment and contribute to the spread of antimicrobial resistance via inhalation or surface contamination (Zhang et al., 2021).

Recent data indicate alarming levels of multidrug resistance among bacteria isolated at the time of cattle slaughter. In *E. coli* isolated from slaughterhouses, resistance to streptomycin (68.7% of isolates), ampicillin (48.7%), and tetracycline (42.5%) predominated, confirming long-term selective pressure in cattle production systems (EFSA and ECDC, 2025a). According to global monitoring systems focused on antimicrobial development, approximately 43.8% of all isolates showed resistance to three or more classes of antimicrobials, thus meeting the criteria for multidrug resistance (GARDP, 2025). ESBL-producing bacteria were detected in 6.3% of slaughterhouse samples, representing a significant risk for subsequent human infections and limiting therapeutic options in human medicine (Trinchera, 2025).

Slaughterhouses represent a critical interface between primary production and the food chain, where diverse bacterial strains meet and may undergo clonal expansion. Transport to slaughter induces a physiological stress response associated with increased cortisol levels, which negatively affects intestinal barrier integrity and promotes shedding of enteric bacteria (Bailey et al., 2011; Bourguet et al., 2015). Experimental studies have shown that environmental stressors can stimulate the bacterial SOS response, a regulatory network enhancing DNA recombination and facilitating HGT (Beaber et al., 2004). Within the gastrointestinal tract, plasmid transfer between members of the Enterobacteriaceae family, including *E. coli* and *Salmonella* spp., has been widely documented, and stress conditions are known to increase the frequency of gene exchange (von Wintersdorff et al., 2016; McInnes et al., 2020). These mechanisms highlight the role of transport and pre-slaughter stress as important drivers of antimicrobial resistance dissemination at the farm-to-slaughter interface.

At slaughterhouse level, one of the major emerging challenges is the persistence of ESBL-producing bacteria. Studies have demonstrated the widespread presence of ESBL-producing *E. coli* in slaughterhouse environments and along the meat processing chain (Telli et al., 2020; Nery Garcia et al., 2025). Particular concern is associated with globally disseminated clones such as sequence type ST131, which combine antimicrobial resistance, virulence traits, and zoonotic potential (Nicolas-Chanoine et al., 2014). Experimental studies have shown that *E. coli* strains can form stable biofilms on stainless steel surfaces commonly used in meat-processing facilities. Biofilm formation significantly increases bacterial tolerance to disinfectants and enables long-term persistence in food-processing environments, facilitating recurrent contamination of carcasses across multiple slaughter days (Cappitelli, 2014; Surgers et al., 2019).

According to the latest ECDC / EFSA surveillance data, resistance levels in *Campylobacter* spp. isolated from cattle at slaughterhouses in some EU regions have reached up to 72% for fluoroquinolones. At the same time, an increasing occurrence of carbapenemase-producing Enterobacteriaceae has been recorded; although historically associated mainly with hospital environments, they are now increasingly isolated from faecal samples of clinically healthy cattle (EFSA and ECDC, 2025a).

The ability of multidrug-resistant bacteria to form complex biofilms on stainless steel, polymer conveyor belts, and other processing equipment surfaces is another key factor in the persistence of AMR in slaughterhouse operations. Bacteria organised in biofilms are significantly protected from commonly used disinfectants, including quaternary ammonium compounds, enabling survival even after standard sanitation cycles and leading to repeated contamination of new meat batches (Ban-Cucerzan, 2025).

Slaughterhouse workers and tools also play a role in AMR dissemination. Equipment such as knives and saws act as fomites; when insufficient sterilisation is performed between carcasses, especially at temperatures below 82°C, clonal strains of resistant *E. coli* can spread throughout the daily production cycle. Studies have demonstrated that slaughterhouse and livestock workers show significantly higher colonisation rates with antimicrobial-resistant bacteria compared with the general population. Molecular epidemiological analyses have revealed genetically related strains of resistant *E. coli* and MRSA in both cattle and exposed workers, indicating bidirectional transmission between animals and humans (van den Broek et al., 2009; Dahms et al., 2015). Occupational exposure to animal faeces, aerosols, and contaminated surfaces has been identified as a key pathway facilitating this zoonotic exchange (Hartung and Schulz, 2011).

The final component of this mechanism is the emission of resistant bacteria and resistance genes into the environment. Slaughterhouses generate large volumes of wastewater containing antibiotic residues, resistant bacteria, and mobile genetic elements. It was confirmed that slaughterhouse wastewater treatment plants often fail to effectively remove class 1 integrons, which subsequently enter surface waters and contribute to the spread of antimicrobial resistance in aquatic ecosystems and wildlife (Savin et al., 2021).

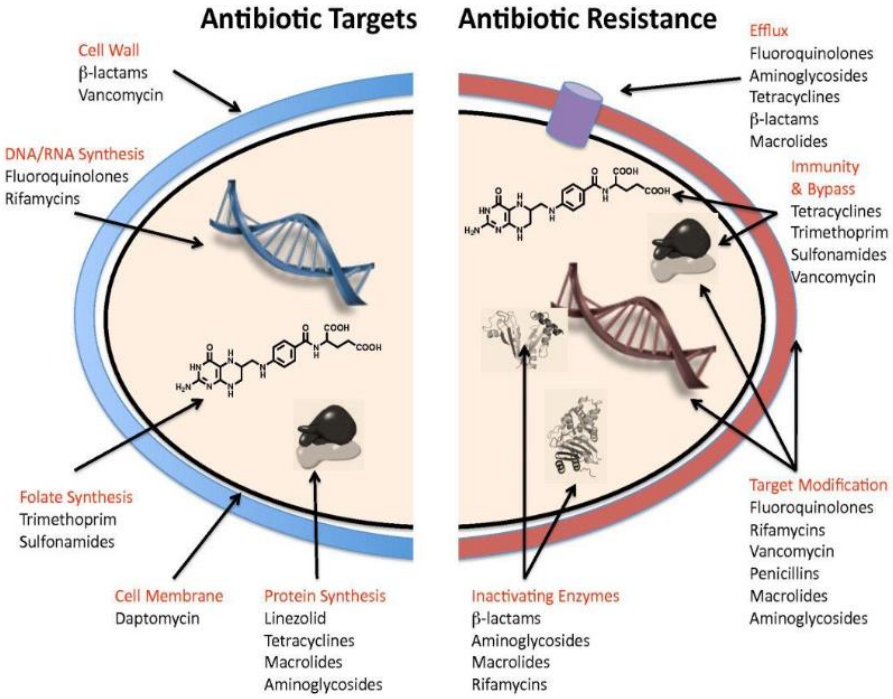


Figure 4 Mechanisms underlying the emergence of antimicrobial resistance

Source: https://www.uvzsr.sk/documents/d/ruvztn/rezistencia-1

4.2.3 Molecular and Environmental Mechanisms of AMR Transmission During Milk Processing

Raw milk and the technological equipment used for its collection and storage, such as milking pipelines, collection pipes and cooling tanks, represent an important environment for the survival and spread of bacteria carrying antibiotic resistance genes. Several studies have demonstrated that raw milk contains complex microbial communities in which resistance genes are located on mobile genetic elements such as plasmids, transposons and integrons, creating conditions for their horizontal transfer between bacteria (Tóth et al., 2020; Liu et al., 2020).

At the molecular level, horizontal gene transfer plays a key role and occurs through conjugation, transduction and transformation. Conjugation is considered the most important mechanism of resistance transfer in dairy systems because it enables the direct transfer of plasmids carrying resistance genes between bacteria in the milk environment. Experimental studies have shown that plasmid-mediated genes, such as the *bla*_CMY-2 gene encoding β-lactamase, can be transferred between *E. coli* strains in raw milk, confirming that milk can function as an active medium for the spread of resistance. In addition to complete plasmids, smaller genetic units such as resistance cassettes or transposons can also be transferred and

subsequently integrated into the chromosome of recipient bacteria (Rossi et al., 2014; Liu et al., 2020).

An important factor promoting the spread of resistance in dairy systems is biofilm formation on the internal surfaces of milk pipelines and collection tanks. Biofilms create a stable microenvironment in which bacteria are in close contact, significantly increasing the likelihood of horizontal gene transfer. At the same time, the biofilm matrix protects microorganisms from the effects of cleaning and disinfecting agents and enables the long-term survival of resistant strains in technological equipment. Isolates of staphylococci and Gram-negative bacteria from milk tanks often simultaneously show the ability to form biofilms and carry multiple resistance genes, highlighting their potential role as reservoirs of resistance (Wiszniewska-Łaszczych et al., 2024).

Raw milk storage conditions, particularly temperature and storage duration, have a significant impact on the dynamics of microbial populations and the resistome. Metagenomic analyses have shown that during raw milk storage the relative abundance of resistance genes may increase even in the absence of antibiotic selective pressure. This phenomenon is explained by the selective advantage of bacteria adapted to cold and stress conditions, which often carry mobile genetic elements (Tóth et al., 2020; Kerek et al., 2023).

From a molecular perspective, bacteriophages present in milk also represent a specific risk, as they may mediate the transduction of resistance genes between bacteria. Although this mechanism has been less studied in dairy systems than conjugation, there is evidence that phage-mediated transfer of resistance determinants may contribute to the spread of resistance in food chains (Rossi et al., 2014).

4.2.4 AMR Monitoring in Cattle

Within the harmonised monitoring of antimicrobial resistance in the European Union, which is also implemented in the Slovak Republic, resistance in cattle is systematically monitored in zoonotic and indicator bacteria in accordance with the EU legal framework. This monitoring is established in Directive 2003/99/EC of the European Parliament and of the Council on the monitoring of zoonoses and zoonotic agents and is carried out according to Commission Implementing Decision (EU) 2020/1729, which sets harmonised requirements for sampling, laboratory testing and reporting of antimicrobial resistance data in the food chain (Commission Implementing Decisions (EU) 2023/1017 and 2020/1729). In cattle, the primary sampling matrix is the caecal content, collected at slaughterhouses after slaughter of clinically

healthy animals, as it represents the main reservoir of the intestinal microbiota and antimicrobial resistance genes and enables comparable assessment of selective pressure across Member States. From these samples, indicator bacteria, primarily *E. coli* as well as ESBL-, AmpC- or carbapenemase-producing bacteria are isolated, serving as sensitive indicators of antimicrobial use in livestock production. The results of monitoring are processed by national reference laboratories and subsequently reported to the joint EFSA and ECDC system, where they form the basis of the annually published summary reports on antimicrobial resistance in the European Union (EFSA and ECDC, 2023).

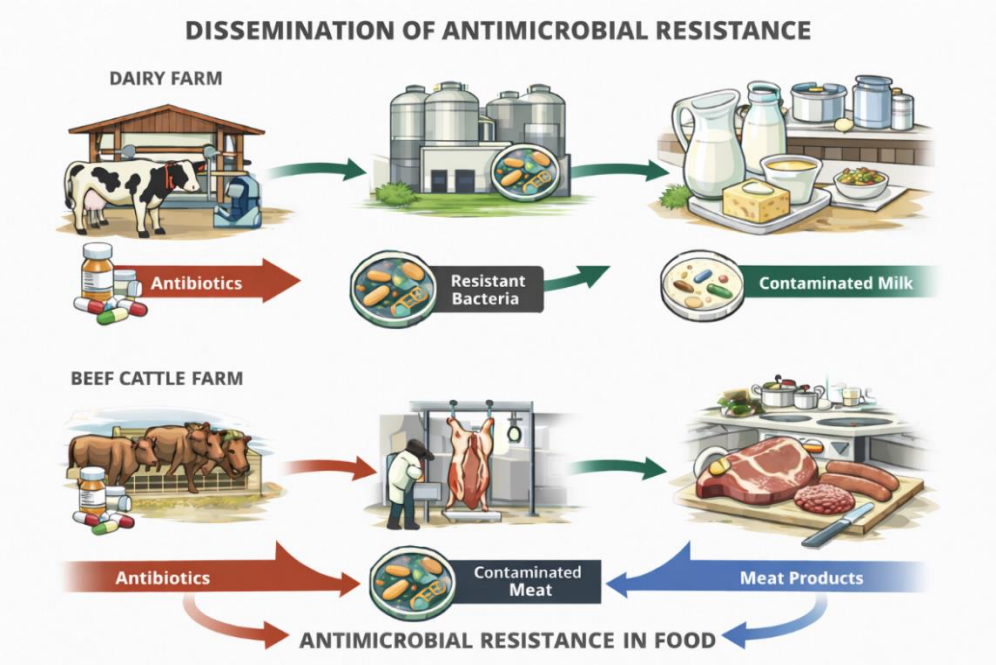


Figure 5 Dissemination of antimicrobial resistance along the dairy and beef production chains

Source: Author's own elaboration based on EFSA and ECDC surveillance data (EFSA and ECDC, 2023).

Unlike intestinal content, milk is not a primary matrix for population-level monitoring of antimicrobial resistance within the EU harmonised system. Milk is not included among the samples designated for evaluating the intestinal resistome under Commission Implementing Decision (EU) 2020/1729; therefore, AMR is not systematically monitored in milk at the population level of food-producing animals (EFSA, 2020; European Commission, 2020). Nevertheless, resistance of bacteria isolated from milk is highly relevant in the clinical and veterinary context, particularly in dairy cow mastitis, where antimicrobial susceptibility testing is performed for isolates such as *Staphylococcus aureus*, coagulase-negative staphylococci,

Streptococcus uberis, Streptococcus dysgalactiae and *E. coli*. This type of monitoring is crucial for the rational use of antimicrobials in dairy herds and for reducing selective pressure promoting resistance development; however, its objective is not population-level AMR surveillance but clinical decision-making and udder health management (EFSA and ECDC, 2023). From a food safety perspective, raw milk in primary production is primarily assessed through hygiene indicators such as total bacterial count and somatic cell count according to Regulation (EC) No 853/2004, while microbiological criteria under Regulation (EC) No 2073/2005 do not apply to raw milk in primary production and are not intended for the assessment of antimicrobial resistance as such (European Parliament and Council of the EU, 2004; European Commission, 2005).

5 Integrated Farm System

Problems in cattle farming are addressed in two main areas: **health monitoring** and **animal identification**. These categories emerged following the analysis of available studies and data. Health monitoring enables accurate assessment of the health status, welfare and nutritional condition of cattle and helps identify potential bottlenecks in nutrition or herd management. Automatic animal identification supports the optimisation of production, management and therapeutic decision-making, thereby indirectly contributing to the reduction of antimicrobial resistance through more targeted treatment (Jiang et al., 2019; Psota et al., 2021).

Health-related challenges in cattle include automated monitoring of behaviour, activity, posture, body conformation, body condition, body weight and respiratory rate, as well as the detection of lameness and mastitis. Identification solutions include facial recognition, breed classification, movement tracking and identification based on muzzle patterns or other distinguishing characteristics (Weber et al., 2020; Xu et al., 2020). At the same time, research focusing on animal identification and monitoring using farm systems for cattle identification and health monitoring has increased significantly in recent years (Psota et al., 2021).

An analysis of research by country showed that the largest number of studies originate from China, followed by Japan and Brazil. This trend demonstrates that the integration of deep learning (DL) technologies with integrated farm systems (IFS) can significantly support efficient herd management, early disease diagnosis and targeted therapy, thereby reducing the risk of excessive antibiotic use and the development of antimicrobial resistance (Jiang et al., 2019; Psota et al., 2021).

Beef cattle production must be not only biologically efficient but also economically sustainable. This includes costs related to housing, feed, veterinary care, labour and infrastructure, as well as production planning (number of farms, production periods and market output). Economic efficiency often requires optimisation of feeding (nutritional balance and the use of available feed resources, including the utilisation of brewer's spent grain as feed), production planning, monitoring of growth and feed conversion, and efficient farm organisation. Farm management must include records of herds, animal origin, health status, preventive measures, feeding records and veterinary interventions. This is important not only from a productivity perspective but also for the traceability of meat and food safety (Ben-Hamed et al., 2011; Ojo et al., 2024).

Integrated Crop-Livestock Farming Systems (ICLFS) combine crop production and livestock farming on the same farm so that the individual components complement each other. By-products from one part of the farm serve as inputs for another. For example, livestock manure provides nutrients for crops and improves soil quality, while crop residues can be used as cattle feed. These systems provide several economic advantages. By diversifying production, small and medium-sized farms can achieve more stable income and reduce dependence on external inputs, thereby lowering production costs. They also increase land-use efficiency and enable higher productivity per unit area while maintaining environmental sustainability. From an environmental perspective, ICLFS reduce soil erosion, support nutrient recycling and increase soil biological activity, contributing to the long-term sustainability of farms. The implementation of such systems supports sustainable cattle production by mitigating negative impacts on water, soil and biodiversity. Successful implementation of integrated systems requires strategic farm management, including appropriate crop selection, pasture renovation, feeding strategies and manure management. Investments in improved pastures, enhanced soil fertility and efficient rotational grazing can significantly influence both profitability and environmental outcomes. Overall, integrated crop-livestock systems provide a model of sustainable cattle farming that enables optimisation of productivity while minimising environmental impacts (Gupta, Rai and Risam, 2012).

For this reason, digital tools are increasingly coming to the forefront, enabling the integration of data on milk production, meat quality, reproduction, nutrition and animal health into a unified management system. Herd management software represents a key element of precision cattle farming used in both dairy and beef production systems. Its application enables not only the optimisation of production parameters but also the early identification of problems that may negatively affect milk and meat quality, farm economics and animal welfare. In this

context, information systems play a crucial role in transforming traditional livestock farming into a data-driven and sustainable production system. The following chapter therefore focuses on the characteristics of herd management software and an overview of its main functions and practical applications in modern farm conditions (Jiang et al., 2019).

5.1 Cattle Monitoring Technologies in IFS

Technology providers aim to integrate all processes into a single system, which we call farm management. It is usually a modular system that we use for managing milking, feeding, automatic cow sorting, hoof care, monitoring activity levels, weighing animals, and so on. The system is designed so that individual modules can be gradually added as needed by the farm. In milk production, modern programs provide a comprehensive view of the entire herd. Timely and clear information helps improve reproductive indicators, health status, milk production, milking parameters, and thus the overall quality of the milk and meat production. Not least, they help to streamline work and optimise costs (UNIFORM – AGRI, 2022).

Herd management software includes the following main areas and functions:

- management decision-making based on comprehensive data,
- simplification of administrative work and improved herd overview,
- complete record-keeping for all animals,
- intuitive and efficient data entry,
- milking process analysis – monitoring milker performance and maximising milking parlour efficiency,
- import of milk recording results and analysis of collected data,
- reproduction analysis,
- reporting of synchronisation protocols,
- health status analysis,
- records of medicines used, veterinary logbook and register of veterinary procedures,
- customisable main dashboard according to the manager's needs,
- possibility of extension with a mobile application and a heat detection and health monitoring system,
- monitoring daily cattle activity,
- determining the optimal time for insemination,
- monitoring cows with reproductive problems,

- identification of animals with reduced movement activity – possible health issue,
- monitoring feeding and rumination time with identification of potential health problems,
- comparison within individual groups and across the entire herd,
- tracking the impact of changes in feeding rations,
- after adding localisation sensors, the position of individual animals can be determined, figure (Uniform – Agri, 2022).



Figure 6 SmartDairy farm management system
Source: UNIFORM – AGRI, 2022

The foundation of accurate livestock breeding is the systematic collection of objective data, which is made possible by sensor systems. Sensors allow continuous monitoring of animals' physiological, behavioural, and environmental parameters, providing a detailed view of their current state and development over time. Unlike traditional visual assessments, sensors deliver quantifiable data that are not influenced by the breeder's subjective perception (Neethirajan, 2020).

In modern farms, various types of sensors are used to monitor animal movement, activity, behaviour, and interactions. Motion sensors and accelerometers enable the detection of specific behaviours, such as lying down, walking, ruminating, or grazing, and changes in these patterns may indicate health or production issues. Camera systems and machine vision technologies provide visual data on animal behaviour within groups and allow for automated analysis using artificial intelligence algorithms (Elbasi, 2023).

Sensors also play a significant role in monitoring microclimatic conditions in animal housing facilities. Environmental sensors track temperature, humidity, gas concentrations, and

air quality, all of which have a crucial impact on the health, production, and well-being of animals. Early identification of unfavourable conditions allows farmers to take corrective measures before negative effects on animals occur (Provolo et al., 2025).

For data acquisition, ground-based sensing systems are most commonly used, such as **RGB cameras, RGB-Depth, RGB** combined with **NIR**, or **thermal sensors**, which provide data for decision-making within the integrated farm system. These technologies are installed above feed bunks, in alleys, near water troughs, or at the exit of the milking parlour, where they provide high-frequency image data suitable for automated processing using artificial intelligence algorithms (Berckmans, 2014; Norton et al., 2019).



Figure 7 Monitoring of cattle behaviour using RGB cameras in housing facilities.

Source: Alves, 2025

RGB cameras are primarily used to analyse cattle behaviour, such as lying time, standing time, locomotor activity, and the use of feeding areas. Changes in these parameters are often the first indicators of health disorders, stress, or reduced welfare. When combined with automated image analysis, RGB systems enable early detection of behavioural anomalies without the need for direct contact with the animal (Guzhva et al., 2018).

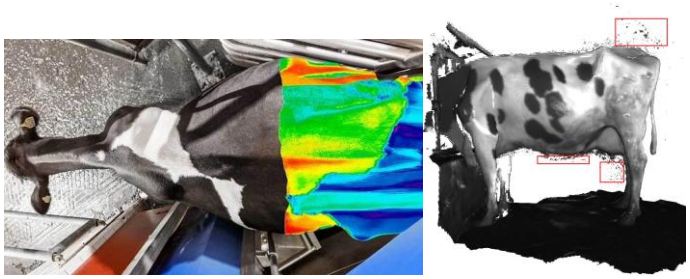
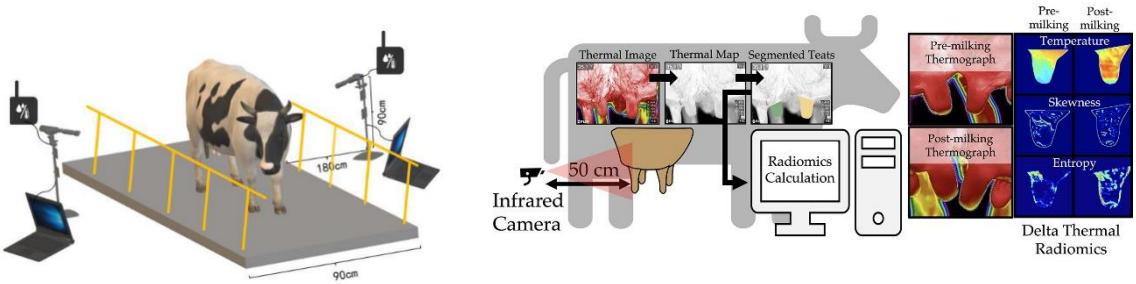


Figure 8 Body condition scoring of dairy cows using RGB-Depth (3D) cameras

Source: https://www.nieuweoogst.nl/nieuws/2021/07/05/camera-heeft-scherpe-blik-op-conditie-koeienNieuwe; Lee et al., 2024

RGB-Depth systems complement colour imaging with depth information, enabling three-dimensional capture of the animal's body. On cattle farms, these systems are mainly used for automated body condition scoring (BCS), detection of changes in back posture, and lameness identification. Their main advantages are higher accuracy and lower sensitivity to lighting conditions and coat colour compared with conventional RGB cameras (Song et al., 2019).



Fiure 9 Thermal imaging of cattle – detection of inflammatory changes and mastitis

Source: Basran et al., 2022; Zhang et al., 2023

Sensors operating in **the near-infrared spectrum** and **thermal cameras** provide information about physiological processes that are not visible to the naked eye. Thermal infrared thermography is particularly applied for the early detection of inflammatory processes such as mastitis, monitoring of body temperature, and identification of heat stress. The combination of multiple types of ground-based sensing systems therefore enables a comprehensive assessment of cattle health status, contributes to reduced disease incidence, and supports targeted and responsible use of antimicrobials in livestock production (McManus et al., 2016; Berckmans, 2017).

The images and videos obtained in this way are processed using deep learning (DL) algorithms, enabling monitoring of the health status, activity, and movement of each animal and supporting decision-making regarding individual therapy, disease prevention, and efficient herd management (Jiang et al., 2019; Psota et al., 2021;). Some studies also used LiDAR, temperature, pressure, or bubble activity sensors. Aerial systems (UAVs / drones) were used in 11 studies, mainly with RGB cameras, and one study used satellite imagery to count cattle (Xu et al., 2020).

Wearable sensing systems also exist, most commonly in the form of sensor collars or ear-mounted devices, and represent an important component of integrated farm systems in cattle

production. These devices enable continuous and individual real-time monitoring of animal behaviour and physiological parameters without the need for restraint or disruptive interventions. Collars are equipped with accelerometers, gyroscopes, microphones, or positioning sensors, allowing evaluation of movement activity, lying and standing time, rumination, feed intake, and social interactions within the herd (Rutten et al., 2013).



Figure 10 Wearable sensor collars for monitoring cattle activity, rumination, and oestrus
Source: Agriland Media, 2026

One of the most important applications of wearable sensors is the automatic detection of oestrus, which is based on increased locomotor activity and behavioural changes in dairy cows. In addition to reproductive management, collars are also used for the early identification of health disorders, as reduced activity, decreased rumination, or changes in daily rhythms often precede the clinical manifestation of disease. The integration of data from wearable sensors with data from ground-based imaging systems and production indicators enables a comprehensive evaluation of animal health and welfare at both the individual and herd levels. Such an approach supports preventive herd management, reduces the need for therapeutic interventions, and contributes to more responsible use of antimicrobials in cattle production (Rutten et al., 2013; Berckmans, 2017).

The widespread use of sensor systems generates a large volume of heterogeneous data in real time. These data are considered big data because they exhibit high volume, velocity, and variety. Their efficient storage and processing require cloud solutions and powerful computing platforms that enable long-term data archiving and subsequent analysis, which is part of smart agriculture (Neethirajan, 2020).

Smart agriculture involves managing farms and operations using technologies such as IoT, robotics, drones, and artificial intelligence to increase both the quantity and quality of

production while reducing the human labour required in farming. AI is a branch of computer science that operates through algorithms based on logical or mathematical models. It has become a crucial part of both scientific research and everyday life. This technology has also expanded into animal husbandry, where modern innovations are making it increasingly difficult to quickly diagnose diseases in livestock and poultry. Currently, diagnosing animal diseases mainly relies on staff and veterinarian observations. However, the human element often delays quick detection and response to changes in animal behaviour, feed intake, defecation and urination patterns, microclimate conditions, and more. Early diagnosis is vital for timely development and implementation of treatment plans (Shubhangi and Neethirajan, 2024).

5.2 Use of AI in Agriculture

The rapid development of modern agriculture is increasingly driven by advanced technologies that enhance productivity and ensure the output of high-quality animal products. Artificial Intelligence has emerged as one of the most transformative forces of the modern era, fundamentally reshaping industries, economies, and societal structures worldwide. Its rapid progress has led to significant improvements in productivity, efficiency, and innovation across diverse sectors such as healthcare, transportation, manufacturing, and education. In the field of **veterinary medicine, AI** and **machine learning (ML)** have become true game changers, particularly in disease diagnostics and continuous livestock health monitoring. These technologies enable the processing of massive datasets (Big Data) generated in real-time by biosensors, diagnostic devices, intelligent surveillance cameras, and automated milking systems. Unlike traditional statistical methods, deep learning algorithms can identify subtle correlations in animal behaviour, such as minute changes in rumination time, movement dynamics, or fluctuations in body temperature. These patterns often elude the human eye but signal the onset of conditions (such as mastitis or lameness) at a subclinical stage. Consequently, AI algorithms facilitate not only the automatic detection of pathological conditions but also the prediction of disease progression and the generation of personalised recommendations for optimal treatment strategies (Neethirajan, 2020; Akinsulie et al., 2024).

This shift toward **Precision Livestock Farming (PLF)** creates new opportunities to improve the accuracy, speed, and accessibility of veterinary diagnostics. Furthermore, integrating AI into farm management reduces the overuse of antibiotics through targeted interventions, directly contributing to the global fight against antimicrobial resistance while elevating animal welfare standards. Ultimately, these systems overcome human resource

constraints, enabling producers to transition from reactive management to a proactive, predictive approach to herd health (De Vries et al., 2023).

Using AI to diagnose internal diseases in animals is especially crucial on large farms, where herd size makes it hard to provide individual attention to each animal. Moreover, these technologies can help lower diagnostic costs, enable early disease detection, and stop their spread. This helps maintain animal productivity, enhances product quality, and reduces antibiotic use, which is essential for environmental sustainability (Ruiz-Real et al., 2020).

It is essential to recognise that integrating AI and ML algorithms into veterinary diagnostics aligns with ongoing trends in the digital transformation of agriculture. Many nations actively promote the development of digital technologies in farming. Utilising these innovative methods can help farms remain competitive in the global market, where product quality and compliance with environmental standards are crucial (Shubhangi and Neethirajan, 2024).

The importance of this topic is also driven by the increasing amount of data in veterinary practice. A large amount of information from various sources, such as veterinary clinics, laboratories, farms, and scientific research, requires specialised tools for analysis and interpretation. Machine learning algorithms can process large volumes of data, detect hidden patterns, and provide real-time recommendations.

5.2.1 Use of Big Data and Machine Learning in Health Management, Production, Nutrition, and Welfare

Large data collected from sensor systems form the basis for applying advanced analytical methods, especially machine learning algorithms and artificial intelligence. These algorithms can process large, complex datasets, identify patterns and relationships within them, and create predictive models useful for managing livestock. One of the most significant areas of machine learning application is early disease detection and prevention. Changes in movement activity, feed intake, body temperature, or vocalisations can signal health issues even before clinical symptoms appear. Predictive models enable the identification of these changes during the preclinical stage of disease, thereby reducing the risk of disease spread, animal mortality, and economic losses. This approach also helps reduce antibiotic use and strengthen preventive health management for animals (Neethirajan, 2020).

Machine learning algorithms are also used to optimise nutrition and increase production efficiency. Feed is one of the largest cost items in animal production, and inefficient use of feed can increase costs and environmental impact. Thanks to precise monitoring of feed and water intake at the individual animal level, feeding rates can be tailored to each animal's current needs,

taking into account age, health status, production stage, and environmental conditions. Such an approach leads to higher feed efficiency, better nutrient utilisation, and improved production results (Cockburn, 2020).

The introduction of advanced technologies into animal production has a significant impact on the assessment and improvement of farm animal welfare. Unlike traditional approaches, which rely on periodic visual inspections, digital technologies enable continuous, objective monitoring of animal behaviour. Analysing movement patterns, social interactions, and responses to the environment provides new insights into animal well-being and allows for early detection of stress, pain, or discomfort. Modern camera systems and image recognition algorithms enable individual identification of animals within a herd without the need for invasive identification methods. These technologies also enable monitoring of animals' behavioural and emotional expressions, shifting welfare assessment from a subjective evaluation to a data-driven process. Improving welfare is not only ethically important but also economically beneficial, as healthy and mentally balanced animals achieve higher production performance and lower disease incidence (Deutch et al., 2025).

Despite significant contributions, the practical implementation of advanced technologies is associated with several challenges. The main issues include questions of data ownership and protection, the technological complexity of systems, and the need for sufficient technical and professional education for farmers. Another limiting factor is unequal access to digital infrastructure, especially in less developed regions. There is also a risk in introducing technologies without adequate verification of their reliability in real-world conditions, which can lead to incorrect decisions and economic losses. Therefore, successful implementation of these technologies requires a systematic approach, collaboration between research institutions, technology companies, and farmers, and clearly defined rules for data management and utilisation (Akinsulie, 2024).

5.2.2 Integration of AI into Dairy Farming

Cow culling is often a result of diseases, where the main risk factors include delayed assistance during calving, abortions, mastitis, lameness, and low fertility rates. The use of artificial intelligence in dairy farming helps improve animal welfare, thereby reducing the risk of disease within the herd. AI-based programs enable real-time video and image analysis for cattle identification, behaviour assessment, clinical condition evaluation, body temperature,

appetite, and feed intake monitoring. Changes in an animal's behaviour can serve as early warning signs of diseases such as lameness or as signs of oestrus (De Vries et al., 2023).

The application of artificial intelligence is also expanding into the management of nutrition and production. By integrating biometric identification with automated feeding systems and milking robots, it is possible to individualise feed rations and optimise milking schedules based on each cow's actual physiological needs. This data-driven approach not only increases milk yield and feeding efficiency but also supports the sustainability of dairy product production (Mahato and Neethirajan, 2024).

Equally important are the implications for large herds, where individual monitoring is otherwise impractical. Artificial intelligence technologies enable farmers to keep personalised records for each cow, making it easier to make more accurate breeding decisions, better monitor reproductive performance, and improve the herd's overall longevity. These systems can also be combined with other smart agricultural tools, such as GPS tracking, to create a fully automated and interconnected farming environment (Lagua et al., 2023).

In recent years, artificial intelligence technologies have been increasingly used to manipulate and manage dairy cows, especially for identification chips and biometric recognition systems such as facial recognition. Traditional herd monitoring methods, based on ear tags or manual observation, have often proven unreliable and labour-intensive, and they also cause additional stress to the animals. In contrast, facial recognition offers a non-invasive approach that enables accurate identification of individual cows and consistent monitoring of their behaviour and health. This innovation not only contributes to herd efficiency but also improves animal welfare, which is becoming a main priority in modern dairy farming (Cockburn, 2020).

By monitoring facial expressions and behavioural patterns, farmers can detect changes in eating habits, social interactions, and the duration of rest or chewing. These indicators serve as early warning signs of potential health issues that are often difficult to recognise through human observation alone. Early detection of mastitis, calving, or metabolic disorders through biometric monitoring can significantly reduce veterinary costs, minimise production losses, and ensure timely interventions that improve the welfare of the entire herd (De Vries et al., 2023).

The integration of AI-based facial recognition and monitoring also presents challenges. Environmental factors such as lighting, weather, or dirt buildup on animals can affect recognition accuracy. Additionally, implementing such technologies requires significant investments in both hardware and software, as well as training farm staff. While continuous

monitoring can improve welfare, it may also alter animals' natural behaviour and the traditional human-animal relationship on farms (Mahato and Neethirajan, 2024).

Japanese researchers Wu et al. (2020) proposed a method for detecting lameness in dairy cattle using artificial intelligence and digital transformation techniques. Another approach involves adapting deep learning algorithms for detecting lame dairy cows using image processing techniques. The authors achieved a detection accuracy of 98.7% and a false positive rate of only 0.03. However, in their dataset, they classified only "lame" and "non-lame" cows, without specifying the degree of lameness.

Fuentes et al. (2020) proposed implementing a model based on individual cow assessment that accounts for changes in environmental indices obtained from an automatic weather station. This model collects real-time information on cows (milk volume and quality) in response to daily environmental conditions and predicts actual feed intake. This information is used to assess heat stress and direct cows to the cooling system to reduce its negative impact.

Casella et al. (2023) have developed a system to predict all stages of bovine respiratory disease in dairy calves. This demonstrated the effectiveness of early diagnosis and relapse prediction in calves with upper respiratory tract disease.

5.2.3 Integration of AI into Beef Farming

Beef cattle production systems (cow-calf, backgrounding and feedlot) are increasingly facing pressure to improve productivity while maintaining high standards of animal welfare, environmental sustainability and responsible antimicrobial use. Unlike dairy farms, where animals are usually housed and intensively managed on a daily basis, beef cattle are often raised in extensive or semi-extensive systems, frequently on pasture and across large areas. This significantly limits direct animal observation, increases the risk of delayed detection of health problems and complicates reproductive management. For this reason, Precision Livestock Farming (PLF), supported by artificial intelligence, is becoming a key tool in modern beef cattle production, as it enables continuous monitoring and data-driven decision-making at both individual animal and herd levels (Fan et al., 2023; Michelena et al., 2025).

One of the major challenges in beef cattle production is the early detection of disease and stress. Respiratory diseases, especially bovine respiratory disease (BRD), are among the most important causes of morbidity, mortality and antibiotic use in cattle production, particularly in feedlot systems. Late recognition often leads to severe clinical cases, higher risk of treatment failure and increased economic losses. AI-based systems that combine sensor data,

video analysis and environmental monitoring can detect subtle behavioural changes such as reduced movement, altered feed intake, increased lying time or reduced social interaction, which may signal disease onset before obvious clinical signs appear. Such technologies support more targeted veterinary interventions, reduce unnecessary antibiotic use and contribute to better antimicrobial resistance control (Menezes et al., 2025; Michelena et al., 2025).

In beef production systems, where frequent individual observation is practically impossible, wearable sensors provide an effective solution. Accelerometers placed on collars, ear tags, or limbs allow monitoring of activity levels (movement, lying, standing), rumination time and feeding-related behaviour. Deviations from normal individual patterns can be evaluated using machine learning models to identify animals at risk, assess stress responses and support objective welfare assessment, particularly during transport, weaning or feedlot adaptation (Lee and Seo, 2021; Ding et al., 2025). These systems generate large continuous datasets suitable for AI algorithms and enable automated behaviour classification and early alerts, significantly reducing reliance on human observation.

Another important area in beef production is nutrition management and performance monitoring. Feeding efficiency and average daily gain (ADG) are crucial for feedlot profitability, while efficient pasture and forage utilisation is essential in extensive cow-calf systems. Artificial intelligence can integrate data from automated weighing systems, feeding stations and computer vision, enabling estimation of body weight, body condition score (BCS) and growth performance without physical animal handling. Computer-vision technologies can extract phenotypic traits from 2D and 3D images and provide non-invasive methods for evaluating body conformation and condition. These approaches are particularly valuable in beef systems, where regular weighing is labour-intensive and stressful for animals (Hou et al., 2023; Guarnido-Lopez et al., 2024).

Artificial intelligence also significantly improves reproductive management in cow-calf systems, where silent oestrus, heat stress and limited observation reduce conception success. As in dairy production, AI-assisted monitoring can recognise oestrus behaviour and increased activity, improving breeding timing and reducing the number of “non-productive days”. In beef herds, these technologies are even more valuable because animals have less human contact and oestrus is more frequently missed. By combining accelerometers and GPS tracking, additional information can be obtained about grazing behaviour, isolation from the herd or reduced mobility, supporting not only oestrus detection but also identification of cows with calving difficulties. AI-based welfare monitoring can therefore indirectly reduce calf losses through earlier dystocia detection and timely assistance. Artificial intelligence is also being integrated

with remote sensing and the digital transformation of grazing systems. GPS collars and AI-driven pasture monitoring can optimise rotational grazing, prevent overgrazing and reduce soil degradation. AI systems can analyse pasture quality, vegetation density and animal distribution, supporting automated decision-making in herd movement strategies. An example of this trend is the development of autonomous herding technologies designed to guide cattle to optimal grazing zones while simultaneously collecting environmental and welfare data, thereby improving productivity and ecosystem sustainability (Harland et al., 2025).

At herd level, AI also facilitates genetic and breeding decisions. In beef production, selection criteria such as growth, carcass quality and feed-conversion efficiency must be balanced with welfare, resilience and fertility indicators. Automated monitoring systems generate large datasets on health events, growth performance and behavioural indicators, enabling the creation of individual animal profiles. These data can serve as inputs for predictive models supporting culling decisions, replacement heifer selection and evaluation of breeding animals. Unlike traditional approaches based on periodic measurements, AI enables continuous phenotyping, which can improve the accuracy of genetic estimates and long-term herd improvement (Jiang et al., 2019; Menezes et al., 2025).

Despite its clear benefits, AI implementation in beef cattle production also presents several challenges. Environmental variability is a major limiting factor, particularly in extensive systems. Changes in weather, lighting, dust or animal contamination can reduce the accuracy of camera systems and biometric identification. In extensive conditions, network connectivity and energy availability are also critical, as sensors require connectivity and battery life suitable for long-term use. Implementation of these technologies is financially demanding, especially for smaller farms, and successful adoption depends on staff training and proper integration into farm management processes. Ethical considerations related to continuous animal monitoring are also discussed, and welfare benefits must be balanced with the preservation of natural behaviour and the traditional human-animal relationship (Menezes et al., 2025; Michelena et al., 2025).

Overall, artificial intelligence represents a major step toward smarter and more sustainable beef cattle production. It enables early disease detection, improves welfare monitoring, optimises feeding and supports reproductive management, thereby reducing economic losses, increasing production efficiency and contributing to responsible antimicrobial use. With the gradual reduction in sensor costs and increasing robustness of models, wider adoption of AI across different beef production systems is expected, moving the sector toward

data-driven livestock production with a strong focus on welfare and farm economic stability (Guarnido-Lopez et al., 2024; Michelena et al., 2025).

6 Algorithmic Modules in IFS

Machine learning algorithms represent a core tool for processing large datasets obtained from sensors, cameras, automated weighing systems, feeding stations and environmental monitoring devices. In beef cattle production, ML models are primarily used for classification and prediction tasks such as early detection of respiratory diseases (e.g., BRD), lameness detection, estimation of body weight and body condition score (BCS), prediction of growth performance, identification of heat stress and optimisation of feedlot management (Banhazi et al., 2012; Neethirajan, 2024; Michelena et al., 2025).

6.1 Types of Machine Learning Algorithms for Beef and Dairy Farm Systems

Decision Tree (DT): A fundamental supervised learning technique, the DT constructs a predictive model in the form of a tree-like, hierarchical structure. Using a set of learned decision rules applied to input features, it recursively splits the dataset into smaller, more homogeneous subsets. Each internal node tests an attribute, each branch shows the test's outcome, and each terminal leaf node indicates a class label or conclusion

Random Forest (RF): The RF algorithm is a sophisticated ensemble technique that constructs many individual trees during training, surpassing traditional decision trees (DT). For each tree, it introduces randomness by using a new bootstrapped sample of the training data and choosing a random subset of features for splitting at each node. The final prediction is then made by combining the outputs of all the trees, which enhances predictive accuracy and helps prevent overfitting. Typically, this is achieved through a majority vote for classification tasks (Lianou, 2024).

Support Vector Machine (SVM): In a high-dimensional feature space, the SVM is a powerful classification method that finds the best separating hyperplane to maximise the margin between different classes. This hyperplane is represented by a line for linearly separable data and by a kernel for non-linear data, which projects the data into a higher dimension where linear separation is possible. To balance the trade-off between maximising margin and reducing classification error, a linear kernel with a regularisation parameter (C) of 3 was used in this experiment (Sarker, 2021).

Light Gradient Boosting Machine (LGBM): LGBM is an extremely effective gradient boosting system designed for speed and performance, especially on large datasets. It builds on DT-based algorithms and incorporates novel techniques, such as a histogram-based approach for finding split points and a leaf-wise growth strategy, that collectively reduce computational overhead and memory usage without compromising accuracy.

Extreme Gradient Bboosting (XGBoost): A highly advanced and optimised version of the gradient boosting method, XGBoost is well-known for its remarkable scalability and performance. It improves traditional gradient boosting by incorporating built-in L1 and L2 regularisation to prevent overfitting, along with advanced features such as parallel processing and cache-aware access, making it a robust and widely adopted algorithm for structured data challenges (Singh et al., 2021).

One-Dimensional Convolutional Neural Network (1D-CNN): As a specialised deep learning architecture, the 1D-CNN effectively processes sequential data by automatically learning hierarchical features. Our implementation included a Conv1D layer, which applies filtering operations to learn local patterns from the input sequence; a MaxPooling1D layer to downsample the feature maps and provide some degree of translational invariance; a Flatten layer to convert the data into a one-dimensional vector; and a final Dense layer for classification.

Long Short-Term Memory (LSTM): An improved version of the Recurrent Neural Network (RNN), the LSTM network was designed specifically to address the vanishing gradient problem and efficiently identify long-range correlations in sequential data. The architecture used in this study comprises a core LSTM layer that manages information flow through gating mechanisms (input, forget, and output gates), a dropout layer for regularisation to reduce overfitting, and a final dense layer to generate the classification output. To ensure that the input features are on a comparable scale, which is essential for optimal performance of distance-based and gradient-based algorithms, the data was standardised before being fed into the SVM, 1D-CNN, and LSTM models. The Standard Scaler function, which scales each feature to have a zero mean and unit standard deviation, was used to complete this preprocessing step (Lianou et al., 2024).

6.1.1 Use of ML Algorithms for Mastitis Detection in Dairy Cows

Machine learning (ML) approaches provide several advantages over traditional diagnostic methods. Unlike traditional single-indicator techniques, machine learning models can consider

multiple factors simultaneously, such as milk yield, milk composition, physiological status, and environmental conditions. They capture complex non-linear relationships to create more comprehensive and accurate prediction systems. Recent developments have further enhanced the scope and sophistication of machine learning applications in dairy farming. Satoła and Satoła (2024) compared ensemble machine learning models (bagging, boosting, stacking) with individual algorithms for predicting subclinical mastitis in Polish Holstein-Friesian cows, showing that support vector machines achieved the highest F1-score (0.760–0.790) across several herds. Tian et al. (2024) developed clinical mastitis prediction models using data on milk yield, rumination time, and electrical conductivity from Chinese dairy farms, with multilayer neural networks and random forests outperforming others on standardised datasets. Thompson et al. (2023) used machine learning to predict SCC status after calving from routine UK milk recording data, highlighting the importance of dry-cow management. The use of time series analysis has also become more prominent, with Guo et al. (2025) exploring XGBoost algorithms combined with SHAP value interpretation for mastitis prediction, achieving both high accuracy and improved interpretability. These algorithm-based systems can process large datasets efficiently without human resource constraints, offering practical herd-wide monitoring solutions.

Despite these advances, current research faces several key limitations that prevent widespread practical use. First, most studies use extensive feature sets that require specialised measurements and equipment (pH meters, electrical conductivity sensors, climate monitoring stations), which may not be available in all dairy operations, especially in resource-limited environments (Norton et al., 2019; Mandujano et al., 2021; Stygar et al., 2023).

Second, many models are built and tested on relatively small datasets or single-farm scenarios, limiting their ability to work well across different farming systems and regions. Third, there is a lack of systematic evaluation to determine whether simpler, more accessible feature sets perform as well or better than complex methods, and no previous study has shown that streamlined approaches using standard farm data can outperform specialised measurements. Lastly, feature importance analysis and model interpretability remain underexplored, hindering the translation of research findings into practical management strategies (Steeneveld et al., 2010; Wieland et al., 2024).

6.2 Types of ML Algorithms Used in Beef Cattle Production

Decision tree (DT): a basic supervised learning method that creates a predictive model in the form of a hierarchical tree structure. Using a set of decision rules applied to input variables, the model recursively divides the dataset into smaller and more homogeneous subsets. Each internal node represents an attribute test, branches represent the outcome of the test, and leaf nodes represent the final class (e.g., "healthy animal" vs. "at-risk animal") or prediction. In beef cattle systems, DTs are primarily used as interpretable models for decision-making regarding health status or the need for veterinary intervention based on behavioural and feed-intake parameters (Quinlan, 1986; Neethirajan, 2024).

Random forest (RF): an advanced ensemble method based on the construction of a large number of decision trees during training. For each tree, a random subset of training data (bootstrap sampling) is used, and at each node a random subset of input variables is selected. The final prediction is obtained by aggregating the predictions of individual trees, typically through "voting" in classification tasks. In beef production systems, RF is suitable for detecting BRD and lameness because it provides robust results even in noisy data, which is common in extensive systems (Breiman, 2001; Michelena et al., 2025).

Support vector machine (SVM): a powerful classification method that searches for the optimal separating hyperplane in the feature space, maximising the margin between classes. For non-linearly separable data, kernel functions transform the data into a higher-dimensional space where linear separation becomes possible. In beef cattle production, SVM is applied to detect behavioural anomalies (reduced activity, changes in feeding rhythm) and to differentiate "sick" vs. "healthy" animals based on multiple behavioural and physiological variables (Cortes and Vapnik, 1995; Neethirajan, 2024).

Light Gradient Boosting Machine (LGBM): an efficient gradient boosting framework optimised for speed and performance when processing large datasets. It uses a histogram-based approach for finding split points and a leaf-wise tree growth strategy, reducing computational demands without compromising accuracy. LGBM is suitable for feedlot data analysis, where large volumes of feeding, weighing, and microclimate data are generated, enabling the model to capture complex non-linear relationships and interactions between variables (Ke et al., 2017).

Extreme Gradient Boosting (XGBoost): an optimised gradient boosting implementation known for high accuracy, scalability, and strong performance with structured data. It includes L1 and L2 regularisation to reduce overfitting and supports parallel computation. In beef production systems, XGBoost can be used to predict BRD risk and

estimate production parameters (growth, feed efficiency) by integrating animal and environmental data. A major advantage is compatibility with explainability tools (e.g., SHAP), facilitating practical application of model outputs (Chen and Guestrin, 2016).

One-dimensional convolutional neural network (1D-CNN): a deep learning architecture designed for processing sequential data. In production settings, inputs may include time series of daily feed intake, activity, or body weight changes. A 1D-CNN automatically extracts local patterns and hierarchical features using convolutional filters. A typical architecture includes a Conv1D layer, MaxPooling1D layer, Flatten layer, and Dense layer for final classification or regression. The model is useful for early detection of behavioural changes prior to clinical disease onset (Goodfellow et al., 2016; Neethirajan, 2024).

Long short-term memory (LSTM): a type of recurrent neural network designed to process long-term temporal dependencies and address the vanishing gradient problem. Through gating mechanisms (input gate, forget gate, output gate), it can retain relevant information over time. In beef cattle production, LSTM is mainly used to predict health status or performance based on time-series data (e.g., activity, feeder visits, weight gain, climatic factors). For proper functioning of distance- and gradient-based algorithms, data standardisation is required, typically using a Standard Scaler (Goodfellow et al., 2016; Michelena et al., 2025).

6.2.1 Application of ML Algorithms for Disease Detection and Welfare Monitoring in Beef Cattle Production

The use of machine learning in beef cattle production offers significant advantages over traditional management methods, which are often based on periodic visual observation of animals and evaluation of individual indicators. Compared with single-indicator approaches (e.g., observing coughing or measuring body temperature), ML models can simultaneously process multidimensional data such as activity time series, rumination time, visits to feeding stations, weight changes, locomotion, thermal comfort and microclimatic factors. This approach enables the identification of complex non-linear relationships and the development of more accurate predictive models of health risks, even at early subclinical stages (Banhazi et al., 2012; Neethirajan, 2024).

In beef production, BRD is a key health challenge and one of the main causes of morbidity, mortality and antimicrobial use in feedlots. For this reason, AI and ML solutions primarily focus on early identification of at-risk animals using behavioural signals (reduced feed intake, social isolation, decreased movement) and physiological indicators (changes in

body temperature, respiratory patterns). This reduces diagnostic delays and supports targeted treatment instead of blanket interventions (Michelena et al., 2025; Menezes et al., 2025).

Lameness detection is another important area, as it is often underdiagnosed in beef systems, particularly in extensive production conditions. Modern approaches use computer vision and deep learning to analyse locomotion patterns, posture and movement asymmetry. Such models can identify gait changes before they become visible to human observers, which is important for both animal welfare and feedlot economics (Neethirajan, 2024; Ding et al., 2025).

In recent years, increasing attention has also been paid to models focused on production efficiency, growth prediction and body condition estimation. The use of ML in combination with automated weighing systems and 3D cameras enables weight estimation without stressful handling of animals, which is particularly useful in beef production systems. These predictive models can improve feeding decisions, optimise feed conversion ratio (FCR) and reduce performance variability among animals (Hou et al., 2023; Guarnido-Lopez et al., 2024).

Despite these advances, several limitations hinder widespread practical adoption. Many studies rely on extensive sets of variables requiring specialised technologies (advanced cameras, automated feeders, weighing systems and climate stations), which may not be available on small or extensive farms. Furthermore, models are often trained on data from a single farm or region, reducing transferability across different conditions (pasture vs. feedlot systems, different breeds, microclimates). Model interpretability and the ability to translate results into simple management decisions remain key challenges for integration into routine farm processes (Hogeveen et al., 2011; Menezes et al., 2025).

6.2.2 Animal Health Indicators Linking Welfare, Production and Beef Quality

The health status of animals in beef cattle production has both direct and indirect effects on the final quality of beef. Diseases such as BRD, chronic inflammation, lameness or prolonged heat stress represent significant stressors that lead to metabolic changes, reduced growth performance and alterations in muscle metabolism. These changes can influence post-mortem muscle pH, meat colour, water-holding capacity and microbial stability during storage (Ferguson and Warner, 2008; Ponnampalam et al., 2017).

From a meat quality perspective, pre-slaughter stress is particularly important, as it may lead to defects such as dark, firm and dry (DFD) meat, characterised by higher post-mortem pH, darker colour and lower market value. Stress associated with health problems, transport,

handling or thermal discomfort increases stress hormone levels and alters muscle glycogen utilisation, thereby directly affecting the technological properties of meat (Ferguson and Warner, 2008; Ponnampalam et al., 2017).

In the context of food chain safety, the treatment of animals with antimicrobial agents is also relevant. In the case of respiratory diseases, which are among the main reasons for antimicrobial treatment in feedlots, there is a risk of antibiotic residues and increased selective pressure for antimicrobial-resistant bacteria. This is important not only for veterinary management but also for meeting legislative requirements for meat safety and AMR control in production systems (Oliver et al., 2011; Arsène et al., 2022).

Therefore, modern precision livestock farming systems increasingly focus on linking animal health data (activity, feed intake, locomotion, heat stress) with production parameters (growth, weight gain, carcass yield) and slaughter indicators. Integrating these datasets into ML models enables the creation of holistic predictive frameworks that support early interventions, optimise fattening strategies and improve meat quality while reducing economic losses (Kamphuis et al., 2008; Liu et al., 2025).

6.2.3 Growth and Body Condition Indicators as Predictors of Meat Quality

Body condition and growth dynamics are among the fundamental indicators of production health in beef cattle. Low or highly fluctuating body condition signals energy deficiency, parasitic or chronic diseases, and impaired welfare, which may translate into lower intramuscular fat and reduced sensory meat quality. Modern computer vision approaches enable automated assessment of BCS and body weight based on 2D / 3D image data, and the outputs can be further processed using ML models to predict carcass traits and meat grading (Hocquette et al., 2011; Guarnido-Lopez et al., 2024).

6.2.4 Monitoring Feed Intake, Activity and Locomotion

Feeding-related behaviour (time at the feeder, visit frequency, intake stability) and locomotion parameters represent important welfare indicators. Reduced feed intake and decreased activity are often the first signals of BRD, metabolic stress or locomotion problems that lead to reduced weight gain and poorer herd uniformity. ML models can use time-series and behavioural profiles to identify at-risk animals before clinical signs appear, thereby supporting early intervention and reducing antibiotic use across the herd (Banhazi et al., 2012; Michelena et al., 2025).

7 Methodology for Implementing an Algorithmic Module for Data-Driven Prediction of AMR

7.1 Definition of the Algorithmic Module and Its Role within IFS

The algorithmic module represents a key component of an integrated farm system designed for both dairy and beef cattle production. In the context of the growing challenge of AMR, its primary objective is to systematically support the reduction and rationalisation of antibiotic use through precise monitoring of animal health, recording of antimicrobial administration, and evaluation of therapeutic effectiveness (Venkateswaran et al., 2024).

The focus of the algorithmic module arises from the need to transition from blanket and preventive antibiotic administration to targeted, individual therapy based on data. The module integrates data on behaviour, physiological parameters, production indicators and animal health with information on the antimicrobial agents used, their dosage, duration of treatment and treatment outcomes. This approach makes it possible to identify situations in which antibiotic therapy can be replaced by preventive or management measures (Rahman 2022).

Within the system, data on the occurrence of diseases typical for both dairy and beef cattle are recorded and analysed, including mastitis, respiratory diseases, locomotor disorders and metabolic disorders. The algorithmic module uses advanced data-analysis methods to detect early changes in health status that may indicate disease development before clinical signs appear. Early intervention enables a reduction in antibiotic use or a shortening of treatment duration (Alcock et al., 2020; Neculai-Valeanu et al., 2024).

An important function of the algorithmic module is the recording and evaluation of antibiotic treatment effectiveness. By linking data on health status, production (milk yield, weight gain) and animal recovery, the effectiveness of individual treatment protocols can be assessed. These insights provide a basis for optimising therapeutic strategies, supporting responsible antimicrobial use and reducing the risk of resistant pathogen development (EMA, 2023; Neethirajan, 2024).

The algorithmic module also supports traceability and transparency within the production chain. Systematic recording of antibiotic interventions is essential not only for herd management but also for food safety, regulatory compliance and consumer trust. The module therefore creates a link between technological solutions, veterinary practice and the principles of sustainable livestock production.

The aim of this chapter is to present the algorithmic module as a tool for combating antimicrobial resistance in dairy and beef cattle production. The following subchapters will focus on its functional architecture, processed data, applied algorithmic approaches and possibilities for practical implementation within an integrated farm system (EMA, 2023; Neethirajan, 2024).

7.2 Objectives of the Algorithmic Module in the Context of AMR

The primary objective of the algorithmic module is to support the responsible use of antimicrobial agents in cattle production in line with AMR mitigation strategies and the One Health concept. The module is designed to minimise the need for antibiotic treatment through early identification of health risks, support for preventive measures and optimisation of herd management. At the same time, it enables systematic monitoring of antibiotic consumption at the level of individual animals as well as the entire herd.

Specific objectives include reducing the frequency of blanket treatments, shortening the duration of antibiotic therapies, identifying recurring health problems and assessing risk factors related to nutrition, housing and environmental conditions. The algorithmic module therefore provides decision support for farmers and veterinarians based on objective data and long-term trends (O'Neill, 2016; WHO, 2017; Krömker et al., 2017; FAO, 2019).

7.3 Functional Architecture of the Algorithmic Module

The algorithmic module operates with several categories of data that together create a comprehensive picture of animal health, production and treatment in herds with both dairy and beef productivity. Health data include information on animal behaviour, activity, body condition, the occurrence of clinical and subclinical diseases, as well as results of preventive examinations. These data are essential for the early identification of health problems that may negatively affect production and lead to an increased need for antibiotic treatment.

Production data in dairy systems primarily include milk yield and quality, milk composition, lactation performance and reproductive indicators. In beef production systems, data are collected on body weight, daily and total weight gains, feed conversion, growth curves and body conformation. These parameters make it possible to evaluate the impact of health status and therapeutic interventions on production performance and economic efficiency.

A specific **category consists of antibiotic-use data**, which include:

- type of active substance,
- dosage,
- route of administration,
- duration of treatment,
- reason for treatment initiation, and
- withdrawal periods.

In dairy production, it is also important to monitor the impact of treatment on milk withdrawal periods, whereas in beef production the main focus is on compliance with withdrawal periods before slaughter. The data system also includes information on the animal's response to treatment, the course of recovery and any recurrence of disease, as recommended by studies focused on monitoring antibiotic use in livestock production (Collineau et al., 2017; Sanders et al., 2020).

The integration of health, production and therapeutic data enables the algorithmic module not only to retrospectively evaluate treatment effectiveness, but also to develop predictive models aimed at reducing the need for antibiotic interventions while maintaining or improving both milk and meat production.

The module operates on the principle of multi-layer data processing, combining sensor data, production parameters, clinical records and laboratory results within a unified database. The aim of this architecture is to transform large volumes of heterogeneous information into practical recommendations usable by farmers and veterinarians. The module input data can be divided into four main groups:

The first group consists of production and reproductive data, such as daily yield, milk composition, number of lactations, lactation curve, postpartum period and other factors influencing the animal's health status and immune response.

The second group includes sensor data and automated measurements enabling early detection of deviations – for example milk electrical conductivity, temperature, activity, rumination time and changes in feed intake.

The third group comprises clinical and veterinary records, particularly the occurrence of mastitis, metritis and other infectious diseases, the course of treatment and previous antibiotic use.

The fourth, key group consists of microbiological and laboratory data, including pathogen identification and results of antimicrobial susceptibility testing (antibiograms).

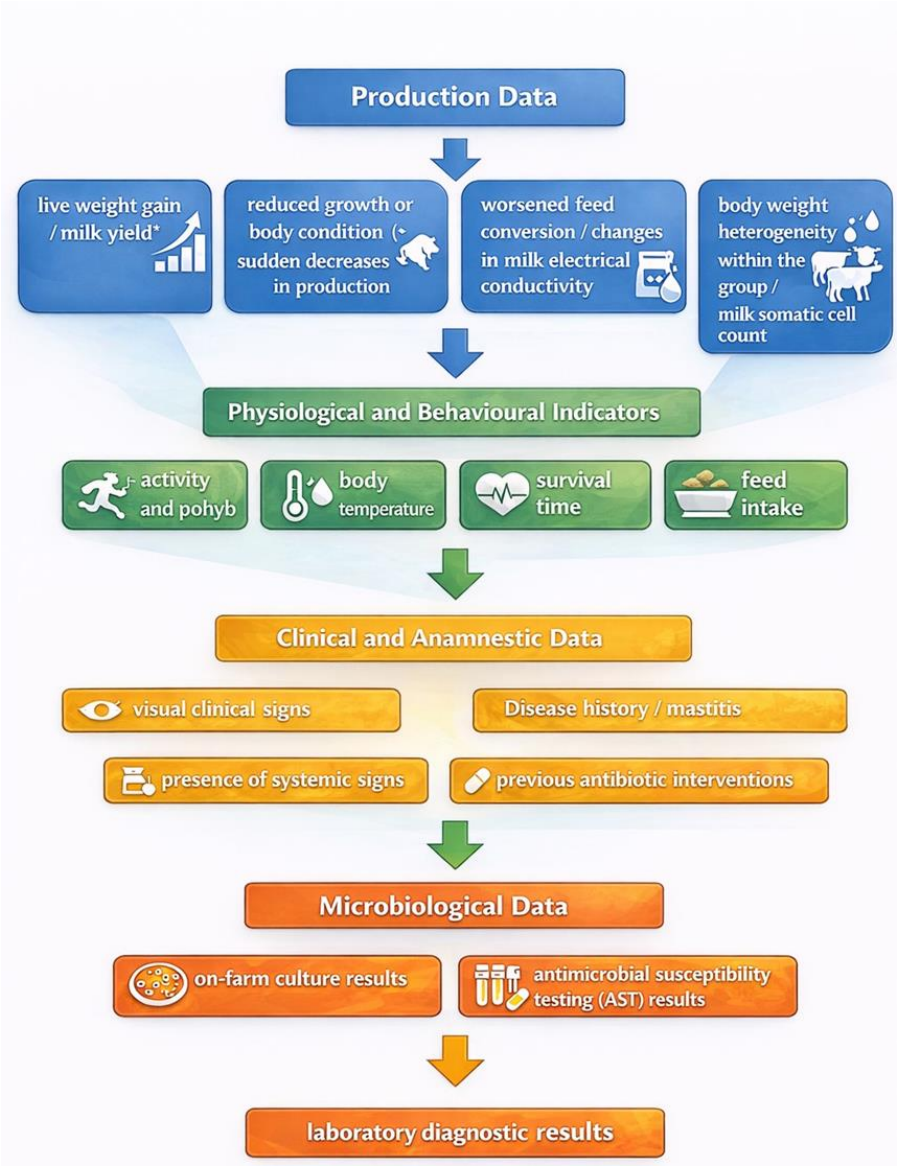


Figure 11 Scheme of processing individual data categories using the algorithmic module

Source: Author's own work

Based on these data, the module performs multi-stage processing:

- **detection and classification** of possible infection,
- **evaluation** of AMR risk using a rule-based or predictive model,
- **proposal** of further actions including diagnostic indication (sampling, culture, PCR, antibiogram),
- **treatment recommendations** in accordance with the principles of prudent antimicrobial use.

The module output is not only a single "decision", but primarily an interpretation of risk in the form of risk categories (low / medium / high risk) and recommendations for appropriate action according to the level of risk and the nature of the infection. Outputs are implemented in the farm system user interface as clear notifications, lists of high-risk animals, trend graphs and summary herd reports.

The module architecture also includes a feedback mechanism enabling the updating of recommendations based on real treatment outcomes and new laboratory findings. This architecture ensures integration between herd management, clinical veterinary practice and laboratory diagnostics, thereby creating a comprehensive system for monitoring and predicting AMR in dairy and beef primary production.

7.4 Practical Implementation Workflow of the AMR Algorithmic Module in Dairy and Beef Herds

Step 1: Data collection and updating (dairy and beef systems)

In the first step, the system continuously collects and updates data at the level of individual animals and the entire herd. In dairy farms, the focus is primarily on parameters related to milk production and quality (daily yield, SCC, electrical conductivity, milk composition), whereas in beef systems the emphasis is placed on growth and production indicators (weight gain, body condition, feed intake, behaviour). Common data for both production types include physiological parameters (activity, rumination time, body temperature), clinical records, and history of previous antibiotic treatments.

Step 2: Detection of health deviation and alert generation

After data acquisition, the module identifies deviations from normal status. In dairy herds, suspected infection may be indicated by increased SCC, higher electrical conductivity, or decreased milk yield. In beef cattle, warning signals include deteriorating body condition, reduced feed intake, decreased activity, or elevated body temperature. When threshold values are exceeded, the module generates an alert and flags the animal or group (pen / feedlot group) as at risk.

Step 3: Preliminary case classification (type of infection and urgency)

In the third step, the algorithm evaluates the probability of infectious disease and assigns an urgency level. The module performs a preliminary classification according to the likely

syndrome, such as mastitis in dairy systems, respiratory disease in feedlots, diarrhoeal diseases, post-partum uterine infections, or skin and limb infections. The urgency level determines the recommended action – monitoring, clinical examination, or immediate intervention.

Step 4: AMR risk calculation (resistance prediction)

A key step of the module is the prediction of antimicrobial resistance risk. The system calculates an AMR score or applies a predictive model based on historical data, considering previous antimicrobial use, recurrent infections, prolonged disease duration, occurrence of resistant pathogens on the farm, and overall antibiotic consumption. The output classifies the case into low, medium, or high AMR risk. High AMR risk indicates a higher probability of empirical treatment failure, and therefore targeted diagnostics are recommended before antibiotic use.

Step 5: Diagnostic decision (sampling and laboratory testing)

Based on the AMR risk, the module recommends the appropriate diagnostic approach. In dairy herds, this typically includes milk sampling and testing for pathogen identification and antimicrobial susceptibility. In beef systems, respiratory swabs, faecal samples, or environmental sampling may be indicated. In high-risk cases, laboratory testing including pathogen identification and antibiogram is recommended to ensure targeted therapy and minimise the selection of resistant strains.

Step 6: Therapeutic intervention and management recommendations

Using the available results, the module proposes a recommended course of action for veterinarians and farmers. In low-risk cases, supportive treatment, animal isolation, and enhanced hygiene measures are prioritised without antibiotic use. In medium-risk cases, selective therapy using narrow-spectrum antimicrobials in accordance with farm protocols may be recommended. In high-risk cases, antibiotic therapy is recommended strictly based on antibiogram results and defined clinical indications. Outputs also include biosecurity measures, withdrawal period monitoring (especially in dairy production), and automatic recording of treatments for auditing and antibiotic-use assessment.

Step 7: Evaluation of effectiveness, reporting, and feedback

The final step involves evaluating intervention effectiveness and updating the data model. The module monitors the return of production parameters to normal (milk yield, SCC) or improvement in health and growth indicators in beef cattle. Treatment outcomes, recurrent

infections, and new microbiological data are stored as feedback. This enables long-term AMR trend monitoring, reporting for veterinarians and farmers, and continuous algorithm improvement with updated herd-specific recommendations.

Continuous feedback and algorithm learning:

- monitors recovery,
- evaluates return to production,
- assesses treatment success,
- updates recommendations for future cases.

This creates a data foundation for optimisation of antibiotic protocols.

Outputs of the algorithmic module:

- recommendation (antibiotics / no antibiotics / delayed treatment),
- proposed next steps,
- antibiotic use records,
- data for AMR reporting,
- decision support for veterinarians.

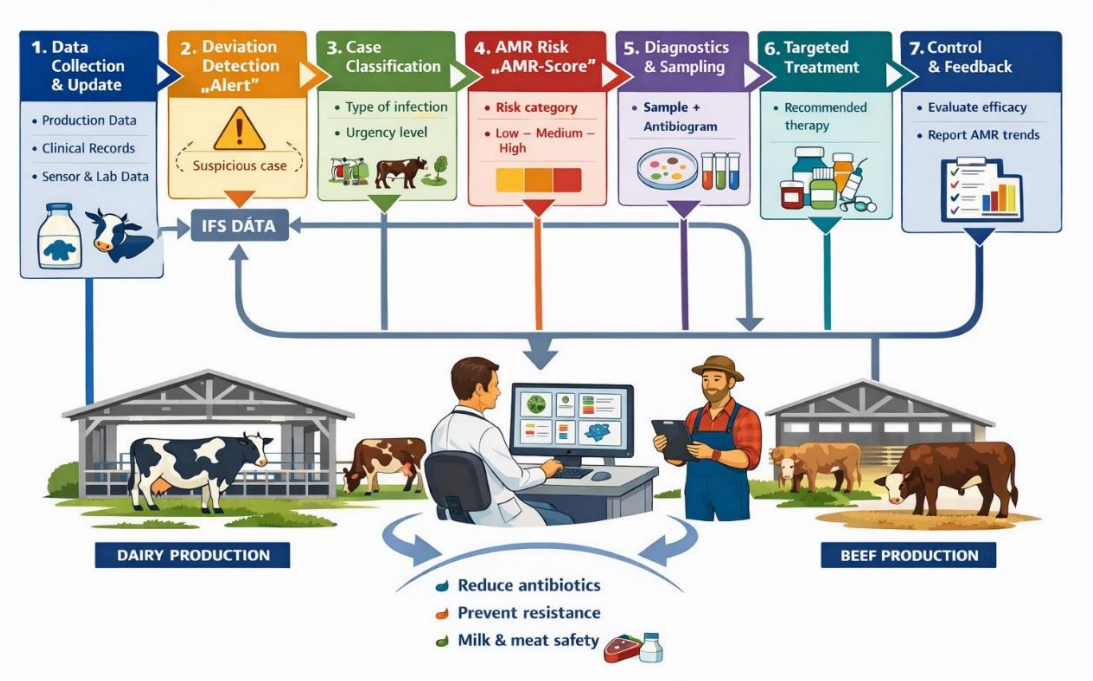


Figure 12 Algoritmic AMR Module – Workflow for Dairy and Beef Production
Source: Author's own work

Practical tool: Simple AMR risk assessment model

AMR-score (0–10 points)

Parameter	Condition	Points
Previous antibiotic treatment (last 90 days)	Yes	+2
Mastitis recurrence	Yes	+2
SCC	>500,000	+2
Milk yield decrease	>15%	+1
Farm AMR history	High	+2
Pathogen	*S. aureus* / resistant strain	+1 to +3

- 0–2 points = low risk → no antibiotics / postpone treatment
- 3–5 points = medium risk → selective therapy
- ≥6 points = high risk → antibiogram mandatory

7.4.1 Model Examples of Algorithmic Module Implementation for Reducing and Monitoring AMR

Model Example A – Dairy Cow with Previous Treatment

Cow No. 148 (2nd lactation, 60 DIM)

- Milk yield drop: 32 → 26 l/day (−19%)
- SCC: 780,000 cells/ml
- EC increased, flakes in milk
- Treated with antibiotics 40 days ago (respiratory infection))

AMR score calculation:

- Antibiotics in last 90 days: +2
- SCC >500,000: +2
- Milk yield drop >15%: +1
- = Total: 5 points → medium risk

Algorithm decision:

- Milk sampling + rapid on-farm culture
- Within 24 h: Gram+ cocci → preliminary targeted antibiotics according to protocol
- After antibiogram: therapy adjustment / de-escalation)

Check after 72 h:

- Clinical improvement
- SCC decreasing trend

Record entered into module → feedback for the system

Model Example B – Dairy Cow without Previous Treatment

On a farm with robotic milking, an automatic alert was generated for a dairy cow (Holstein–Friesian, 2nd lactation, 65 DIM).

The system recorded:

• milk yield decrease from 34 l/day to 28 l/day (-18%),

• increased electrical conductivity of milk,

• abnormalities during milking,

• increased SCC from the latest milk recording.

These data represent a typical example in which the algorithm can detect potential subclinical or early clinical mastitis before obvious clinical signs appear, while the subsequent decision-making must focus on rationalising antibiotic intervention.

Step 1 – Case classification (severity)

• no fever, udder without pronounced swelling,

• only mild flakes present in milk,

→ classification: *mild to moderate course.*

Step 2 – AMR score

• antibiotic treatment within the previous 90 days: NO (0)

• mastitis recurrence in this cow: YES (+2)

• high SCC: YES (+1)

• previous resistant isolates in the herd: NO (0)

→ *AMR score = 3 (moderate risk)*

Step 3 – Diagnostics

The algorithm recommends:

• aseptic milk sample collection,

• on-farm culture or laboratory submission,

• therapy decision based on pathogen confirmation and farm protocol.

This approach corresponds with the practical use of bacteriological culture in mastitis management, where negative results or Gram-negative aetiology often allow avoidance or postponement of antibiotic therapy.

Step 4 – Treatment decision

Culture result:

- no growth / negative finding.

Algorithmic recommendation:

- do not initiate antibiotic therapy,
- supportive treatment (NSAIDs if needed),
- intensified monitoring of SCC and EC for 48–72 h.

When culture is negative, postponing or avoiding antibiotic treatment is rational, as antibiotic therapy without an identified bacterial pathogen increases selective pressure without proven benefit.

Step 5 – Feedback

After 72 hours:

- milk yield stabilised (31 l/day),
- EC returning to normal,
- clinical signs resolved.

Outcome:

- case labelled as *"self-limiting / resolved without antibiotics"*
- stored in the database as a positive algorithm outcome.

Model Example C – Feedlot Beef Cattle with BRD

On a feedlot farm (e.g., Charolais / Limousine crossbreeds), during the first 14 days after arrival / transport, the following were recorded:

- reduced activity and feed intake in several animals
- coughing and nasal discharge in part of the group
- increased respiratory score

This situation is typical of the bovine respiratory disease complex (BRD), one of the main reasons for antimicrobial therapy in feedlots and therefore strongly associated with the risk of selecting resistant strains.

Step 1 – Case classification (severity)

- 1 animal: dyspnoea, marked depression (*severe*)
- 4 animals: mild to moderate respiratory signs

→ *the algorithm identifies a cluster and activates group evaluation mode.*

Step 2 – AMR score (for the index animal)

- previous antibiotic treatment: YES (+2) *(metaphylaxis on arrival – if applied)*
- recurrence of respiratory disease: NO (0)
- high-risk pathogen on farm / in region: *Mycoplasma bovis* (suspected) (+2)
- deterioration in body condition / feed intake: YES (+1)

→ *AMR score = 5–7 = moderate to high risk*

Step 3 – Diagnostics

Recommended:

- nasal swab or tracheal wash sampling (according to practice),
- rapid PCR / identification if available,
- culture and antimicrobial susceptibility testing (at least at group level)

BRD epidemiology highlights the multifactorial nature of the disease; therefore, diagnostics are crucial particularly in recurrent outbreaks and treatment failures.

Step 4 – Therapeutic approach

• Index animal (severe): antibiotics according to protocol + NSAIDs, isolation

• Other animals (mild): monitoring for 24 h + symptomatic support

• Group treatment / metaphylaxis: only if the algorithm detects rapid spread and high probability of losses

This selective model reduces the risk of blanket antibiotic administration while maintaining welfare in severely affected animals.

Step 5 – Monitoring and feedback

After 7 days:

- if >80% of animals show no clinical signs → case closed
- if the problem persists → the system:
- increases risk weighting for future animal movements,
- recommends adjustment of preventive measures (ventilation, vaccination, quarantine).

This workflow follows the principles of recording, effectiveness evaluation and feedback, which form the core of the algorithmic module.

8 Conclusion

Global population growth, limited availability of production resources, and changing climatic conditions will increase the pressure for efficient and safe production of milk and beef in the coming decades. In this context, the management of antimicrobial resistance in cattle production is becoming a key factor in the sustainability of livestock production systems.

Algorithmic modules integrated into farm information systems enable a data-driven approach to monitoring animal health, rationalising antimicrobial use, and evaluating the effectiveness of therapeutic interventions. The integration of sensor technologies, automation, and standardised decision-making procedures creates the conditions for further reduction of selective pressure without negatively affecting production or animal welfare.

In the conditions of the Visegrad Group countries, this approach represents a practical framework for adapting cattle farming to future production and environmental challenges while maintaining the effectiveness of antimicrobial therapy.

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Department of Food Hygiene, Technology and Safety, University of Veterinary Medicine and Pharmacy, Košice, Slovakia

Research and Academic Experience: Expert in laboratory technologies in the field of physico-chemical methods and separation techniques used in food analysis. She is professionally engaged in microbiological food analysis, focusing on the identification of pathogens and potential pathogens in food through quantitative and qualitative examinations using culture-based methods. Her research activities also address disinfection in the food industry, with the aim of developing new-generation disinfectants with a broad-spectrum effect. Her teaching activities include courses focused on the hygiene of milk, dairy products, and plant commodities within veterinary and food production study programmes.

Research Area: Her research focuses on microbial pathogens in animal production systems, with particular emphasis on antimicrobial resistance in food-producing animals. She is involved in the identification and microbiological analysis of pathogens and potential pathogens in food, contributing to the assessment of food safety and microbiological quality within the food production chain.

Number of Published Papers and Citations: She is the author and co-author of 182 scientific publications, 34 of which are indexed in the Scopus and Web of Science databases. Her research focuses on antimicrobial resistance and the detection of pathogenic bacteria in food and animal production systems. Her work is widely cited, reflecting her contribution to the fields of veterinary and food microbiology. Across all databases, 488 citations have been registered and her Hirsch index is 12.

Research Projects: Principal investigator of a Slovak research project focused on the research and implementation of new strategies for the control and reduction of antimicrobial resistance in animal production systems. To date, involvement as responsible investigator, deputy responsible investigator, and co-investigator in several additional grant projects funded by ERASMUS+, APVV, VEGA, and KEGA.

Ivana Regecová, assoc. prof., DVM., Ph.D.

Department of Food Hygiene, Technology and Safety, University of Veterinary Medicine and Pharmacy, Košice, Slovakia

Research and Academic Experience: Expert in the detection of microbial pathogens in animal production systems with a focus on antimicrobial resistance in food-producing animals. Specialist in microbiological diagnostics and molecular methods, particularly PCR-based detection of pathogens and resistance determinants. Teaching activities include meat hygiene, food microbiology, and food legislation within veterinary and food production study programmes.

Research Area: Her research focuses on the detection and characterization of microbial pathogens in animal production systems, with particular emphasis on antimicrobial resistance. She specializes in microbiological diagnostics and molecular methods, especially PCR-based detection of pathogens and resistance genes. Her work also includes the assessment of microbiota, mycobiota and the microbiological quality of food of animal origin in relation to food safety and public health.

Number of Published Papers and Citations: She is the author and co-author of 178 scientific publications, 34 of which are indexed in the Scopus and Web of Science databases. Her research focuses on antimicrobial resistance and the detection of pathogenic bacteria in food and animal production systems. Her work is widely cited, reflecting her contribution to the fields of veterinary and food microbiology. In all databases, 545 citations are registered, and the Hirsch index is 13.

Research Projects: Principal investigator of one international and one Slovak research project focused on the detection of microbiota, mycobiota and antimicrobial resistance in animal production. She is also a co-investigator in 2 international and 7 Slovak research projects.

Activities: Since 2018, she has been a member of the Slovak Society for Agricultural, Forestry, Food and Veterinary Sciences at the Slovak Academy of Sciences in Bratislava. She also serves as an external expert of the Slovak National Accreditation Service (SNAS).

František Zigo, assoc. prof., DVM., Ph.D.

Department of Nutrition and Animal Husbandry, University of Veterinary Medicine and Pharmacy, Košice, Slovakia

Research and Academic Experience: Knowledge and methodological skills in the field in detecting of udder pathogens, their virulence factors and health safety of milk produced. Teaching activities on animal husbandry and technology of animal production.

Research Area: Research activities aimed at solving problems in the field of ruminant breeding and primary milk production, as well as poultry, pigeon and rabbits breeding and diseases. His current scientific interests include mastitis-pathogen, stress biomarkers and alternative therapeutics in dairy animals.

Number of Published Papers and Citations: He is a author of academic book titled "Occurrence of Mastitis in Dairy Herds and the Detection of Virulence Factors in Staphylococci", to be published by IntechOpen, UK. His work is widely cited, reflecting his growing influence in the fields of veterinary science and chemical biology. The scientific achievement consists from 250 peer-reviewed scientific publications, and 102 of them in SCI/WoS and Scopus, 2 monograph and 6 text books. In databases WoS and Scopus, 815 citations are registered, and the Hirsch index is 15.

Research Projects: The main researcher of 2 foreign and 4 Slovak projects focused on the detection and prevention of mastitis. Co-solver of 2 foreign NAWA project (Poland) and 4 Slovak projects.

Special Award: Inclusion and publication of a CV in the Encyclopedia of Personalities of the Czech and Slovak Republics, 2018, British Publishing House based on the BP index. Member of the editorial board of the International Journal of Avian & Wildlife Biology.

dr hab. Andrzej Łozicki, prof. SGGW

Department of Animal Breeding and Nutrition, Institute of Animal Sciences, Warsaw University of Life Sciences (SGGW), Poland

Research and Academic Experience: His research interests include feed preservation, animal nutrition, the effects of nutrition on animal health and the quality of animal products, and the

mitigation of emissions from animal production through appropriate feeding strategies. His teaching activities include courses on feed preparation and preservation, the production and use of feed additives in animal nutrition, and the nutrition of different farm animal species.

Research Area: His research focuses on feed preparation and preservation technologies and on the development of novel feed additives for farm animals, particularly cattle. His main research areas include nutritional strategies for dairy and beef cattle aimed at improving the quality and nutritional value of milk and meat, enhancing immune function, supporting the health and welfare of calves, dairy cows and beef cattle, and reducing emissions associated with milk and beef production. He is also involved in research on the nutrition of geese, snails, and insects used for feed production.

Number of Published Papers and Citations: His scientific output includes 89 peer-reviewed publications, including papers indexed in the SCI/WoS and Scopus databases. He is also a co-author of five patents. His publications have received 259 citations according to WoS and Scopus, and his Hirsch index (h-index) is 10.

Research Projects: He has participated in 12 research projects, including four as research leader. The projects included the evaluation of the nutritional value and feeding suitability of dried distillers grains with solubles (DDGS) for dairy and beef cattle, the effects of forage ensiling methods on silage quality and the content of bioactive compounds, the impact of nutrition on the quality and nutritional value of milk and meat, the use of minerals in nanoparticle form in broiler nutrition, the optimisation of rearing conditions for the snail Helix aspersa Müller, and the assessment of duckweed from biorefineries as a feed ingredient for cattle. In recent years, his research has focused on the use of agri-food industry by-products in beef cattle feeding, the optimisation of beef cattle nutrition to reduce nitrogen emissions to the environment, and the stimulation of immune function and reduction of stress (including heat stress) in young beef cattle through feed additives. The projects were funded by national and European Union sources.

Special Award: He has received several individual and team awards from the Rector of the Warsaw University of Life Sciences (SGGW) for scientific, teaching and organisational achievements. He was also awarded the honorary badge “Meritorious for Agriculture” by the Minister of Agriculture and Rural Development of the Republic of Poland.

Petr Sláma, assoc. prof., Ing., Ph.D.

Department of Animal Morphology, Physiology and Genetics, Mendel University in Brno, Czech Republic

Research and Academic Experience: Expertise in immunology, cell biology, and cell culture techniques, with a focus on detecting inflammatory cytokines related to mastitis. Teaching responsibilities include courses in animal anatomy, physiology, and immunology.

Research Areas: Research primarily focused on Animal science, immunology, mammary gland, mastitis, phytonutrients, 3D cell culture.

Publications and Citations: Author of 128 articles peer-reviewed publications indexed in the Web of Science Core Collection. These works have received 2200 citations, with an H-index of 24.

Research Projects: Principal investigator of two Czech and two international projects focused on mastitis and phytonutrients. Co-investigator in an additional two Czech and two international projects.

Special Award: he has been included in the stanford university–elsevier list of the top 2% most cited scientists worldwide (2024), based on citation data from the scopus database.

Juliana Arvaiová, Ing.

She is a doctoral researcher at the University of Veterinary Medicine and Pharmacy in Košice, Slovakia. Currently based at the Department of Animal Nutrition and Husbandry, her work bridges the gap between theoretical research and practical application in modern farming systems.

Research Experience: Her research profile is focused on Animal Science and the hygiene of milk primary production, with a specific specialization in bovine mastitis management. She is actively involved in projects (e.g., APVV and VEGA) aimed at developing alternative methods for mastitis control to reduce reliance on antibiotics in livestock farming.

Academic Experience: Together with her supervisor František Zigo, she works on implementing new scientific knowledge into teaching students in the subject of Animal Husbandry.


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