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Editorial

Production: Animal Nutrition and Farm Systems

Invited Reviews

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Invited Reviews

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Editorial

The Future of Dairy: Introduction

Matthew C. Lucy*

We live in unprecedented times in dairy science, where opportunities and challenges to our industry arise with increasing frequency and from unexpected places. Some of the opportunities come from new technologies that take our industry in new directions. The beef-on-dairy phenomenon (Berry, 2021) is a good example of this, where improved reproduction in dairy herds, the widespread application of sex-selected semen, and a drought that depleted the US beef herd came together to create a lucrative market for crossbred dairy calves. Some challenges come from the simplest life forms on the planet with the capacity to rapidly infect huge populations of wild and domestic species, including dairy cattle (e.g., highly pathogenic avian influenza [HPAI] or H5N1; McArt, 2024). Our understanding of this new organism is so limited that we do not know how the virus efficiently travels from farm to farm, nor do we know why some animals are severely affected while others remain asymptomatic.

The beef-on-dairy and HPAI examples are remarkable in the speed with which they overtook the dairy industry. Both can be traced back to events that occurred within the last 5 to 6 yr (historic droughts beginning in 2020 that depleted the US beef herd and the introduction of HPAI into the United States in late 2021 with a spillover event into dairy in the spring of 2024). Given the speed with which the dairy industry can change, the American Dairy Science Association and the editors of *JDS Communications* have embarked on an effort to periodically assess the state of dairy research through a series of invited reviews. These reviews will address the existing and emerging trends in the dairy industry and the new technologies that have the capacity to create transformative change. This special issue represents the first in a series of special issues that will be assembled at approximately 5-yr intervals to address the rapid evolution of science that supports an ever-changing dairy industry.

The 2025 special issue includes 8 invited reviews that cover some of the most rapidly evolving topics in the dairy industry. Three papers address the future of traditional subjects in the dairy sciences (udder health, reproduction, and genetics). The conclusion of the first is that mastitis treatment should emphasize antimicrobial stewardship and not unproven or poorly tested alternatives to antimicrobials (Ruegg, 2025). The second paper examines emerging technologies that have the capacity to change the way we achieve pregnancy (Lucy, 2025). This paper also outlines challenging new areas of research with long-term implications for dairy reproduction. The third paper examines the "cow of the future" with respect to the specific traits that will define this cow (Brito et al., 2025). Phenomics (using data from automated devices in the development of reliable phenotypes used in genomic selection) will play a large role in this process.

Two papers examine new areas of research that will assuredly see greater emphasis in the future. The first highlights the importance of the perinatal period (final 2 mo of gestation through the first 2 mo of life) in the development of the mammary gland and its effects on the lifetime performance of the cow (Laporta and Guenther, 2025). As pointed out by the authors, critical windows of development for tissues that support lactation typically occur when the animal is not lactating. Future performance is heavily dependent on these developmental periods. A second paper (Proudfoot et al., 2025) addresses dairy cattle cognition, that is, can dairy cattle acquire, process, store, and act on information from the environment? Generating new knowledge on this topic and adapting our management practices so that they align with dairy cattle cognition is essential if we expect to maintain the support of consumers (Jiang et al., 2021). A sixth paper in this special issue addresses the consumers of the future and their expectations of dairy products (Pollet, 2025). This will include tailoring the food that they eat to their personal preferences for health, wellness, and consciousness.

Two final papers address the future of dairy management in the age of "big data" and artificial intelligence. Modern dairy farms are increasingly "data-genic," and the integration of datasets from diverse sources will define the future of dairy. As detailed in the first paper (Hostens et al., 2025), artificial intelligence will play a major role in decision-making on large farms. Powerful models will be developed to support this decision-making process. One such model, named "RuFaS," is presented in the second paper (Reed et al., 2025).

I appreciate the efforts of the authors, reviewers, and editors in the creation of this special issue on the future of dairy and look forward to future special issues in *JDS Communications* that periodically review the state of dairy science.

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The list of standard abbreviations for JDSC is available at adsa.org/jdsc-abbreviations-25. Nonstandard abbreviations are available in the Notes.

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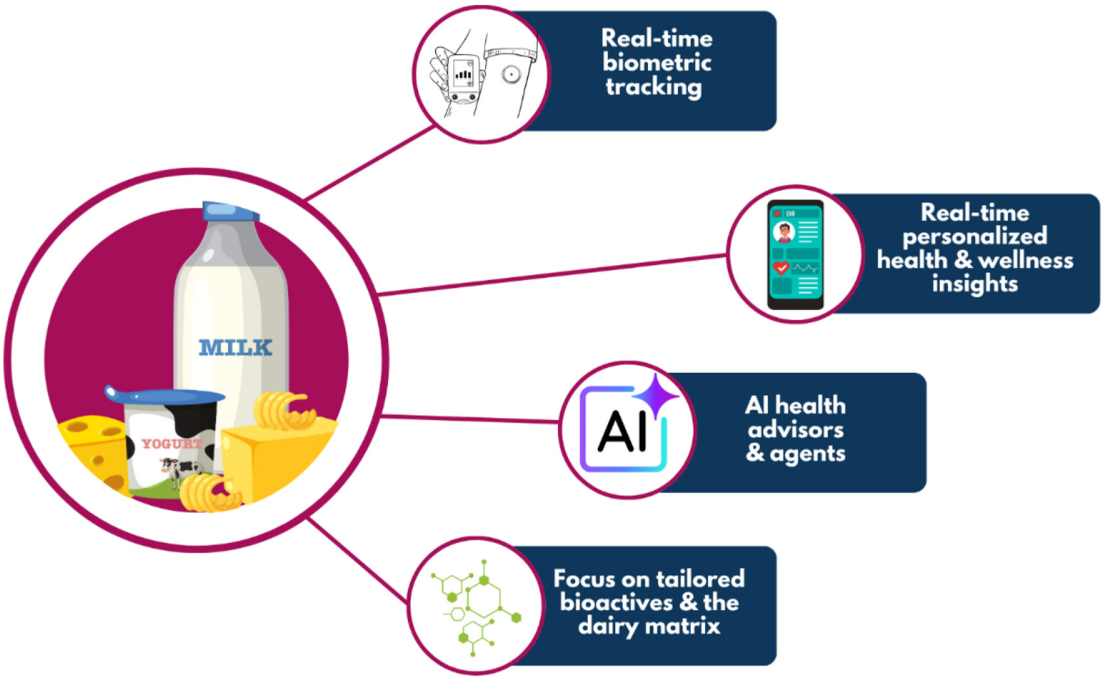
Editorial

The future of milk in 2050: Dairy in the age of personalization

Eve Pollet*

Graphical Abstract



Summary

In the past 25 years, dairy has continued to be recognized as a highly nutrient-dense commodity. Advancements in the next 25 years will push culture and consumers toward enhanced demands for precision, personalization, and transparency—from the products they purchase to the services they use—especially regarding food, health, and wellness. This may begin the shift for dairy and milk from a nutrient-dense commodity to an even higher-value food. Dairy foods may need to align with new concepts in the future of retail and commerce that allow consumers to gain tailored solutions based on criteria and personal preferences they set, with and through their own technology. Dairy science will play a critical role in enabling this shift—encompassing fields from nutrition science and product development to genetics, marketing, and commercialization—by leveraging the versatility of milk and demonstrating dairy's health and wellness benefits from the molecular level to the whole dairy matrix. Graphical abstract created in Canva Pro.

Highlights

- In the near future, customization and personalization may help fill knowledge gaps around nutrition, providing consumers with accessible and credible information based on their own biological data.
- Dairy's wide array of bioactives and macro- and micronutrients makes it a powerful, nutrient-dense product for a future in which health and wellness solutions are increasingly tailored to individual needs.
- The dairy industry should seek to leverage technology to provide consumers with the science-backed products that serve a variety of personal health and wellness needs.

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Editorial

The future of milk in 2050: Dairy in the age of personalization

Eve Pollet*

Abstract: Cow milk is often considered one of the most versatile foods on the planet, with an ability to transform into multiple formats, containing thousands of bioactive compounds that serve a plethora of different purposes in the body, some of which are known, and many of which are still to be discovered. In the past 25 years, dairy has continued to be recognized as a highly nutrient-dense commodity. Advancements in the next 25 years will push culture and consumers toward enhanced demands for precision, personalization, and transparency from the products they purchase to the services they use, especially regarding food, health, and wellness. This will begin the shift for dairy and milk from a nutrient-dense commodity to an even higher value food. Dairy foods will need to align with new concepts in the future of retail and commerce that allow consumers to gain tailored solutions based on a set of criteria and personal preferences they set, with and through their personal technology. Dairy science will play a critical role in enabling this shift—encompassing fields from nutrition science and product development to genetics, marketing, and commercialization—by leveraging the versatility of cow milk and demonstrating dairy food's health and wellness benefits from the molecular level to the whole dairy matrix.

Personalization and customization will become a driving force for change in the future, enabled by technology and affecting every industry. This article will review how technology is driving future consumer and cultural expectations toward receiving personalized recommendations, products, and services in the next 25 years. This article will examine how personalization will affect health and wellness, food and beverage, and retail. It reviews technologies, companies, and concepts that exist today that are driving this future such as those in precision health and nutrition, and how dairy science could play a critical role in this shift.

Today's average consumer under 40 yr of age has grown up in an era of constant technological advancement, experiencing important upgrades in consumer technology nearly every year. This single truth has shaped their lives, expectations, and the role of brands and food and beverage in their lives. Using a single example, since 2011, Apple has consistently released a new iPhone every year (Grothaus, 2025), setting a new expectation for consumers and culture across all categories beyond their technology: that quality upgrades are a new norm, and as a result, upgrades are a constant expectation for brands and categories. This has certainly translated to food and beverage like it has in other categories. This concept of the consistent upgrade as a norm and expectation plays out in consumer trends, consumer expectations, and behaviors. Today, novelty is the norm. Convenience and constant connection and access to the internet, to information, and to others is a baseline expectation for consumers today. As a result, attention has become the new currency in branding and business for quite some time, driven by the constant evolution of technology and digital tools (Davenport and Beck, 2002). Consumers expect upgrades from their brands, new and novel ways of enjoying them, and new features, and more recently, they have come to expect products and services to better serve their precise and contextual needs and desires. Whereas today novelty is a norm and convenience and constant connection is a baseline expectation, as we make our way to 2050, the new consumer and cultural expectation will be around personalization and customization. Today, consumers are getting personalized recommendations based on their past purchases and current needs and preferences, whether it is a targeted advertisement on their social media to a recommendation from a retailer like Amazon, or a search on Perplexity AI on what they should eat or do that returns results based on their stored personal preferences. The ability for technology to personalize product recommendations to consumers, and the ability for consumers to customize a product or experience to their specific needs and preferences will not only become a baseline expectation in the future, but it will also become a differentiator for industries, companies, and brands. Today, when consumers lack complete knowledge on products or solutions that meet their specific needs, they often give their attention to their friends, social media, and related forums or influencers to help them find solutions. This can lead to misinformation, especially when it comes to food, beverages, and supplements. A 2024 consumer survey by company MyFitnessPal and a follow-up study with MyFitnessPal and Dublin City University found that only 2.1% of nutrition trends shared on the social media site TikTok provided accurate information when compared with public health and nutrition guidelines (Dublin City University and MyFitnessPal, 2024). The survey also highlighted that 87% of Millennial and Generation Z TikTok users have turned to the platform for nutrition and health advice. For those who have been influenced by nutrition and health trends on TikTok, 67% report they adopt at least one of these trends, sometimes called "hacks," a few times a week (Dublin City University and MyFitnessPal, 2024).

In the next 25 years, customization and personalization will help to fill knowledge gaps around nutrition, ensuring that consumers do not need to "hack" their way to solutions, by simply providing the right solutions that already exist—recommendations designed

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directly from the consumers' health and personal data sources, or their personal "source of truth." New "personalized sources of truth" will have an impact on all industries, including food and beverage. They may drive new design of foods, supplements, or formats that fit consumer needs and push for a more agile infrastructure to service personalized products, from packaging to product delivery, and to product contents. Or, they may simply outline what seems to be customers' top areas of need, which require more evolved products to serve them adequately.

Although personalization will affect every area of life in the future, its impact on the health and nutrition may be one of the most exciting areas for dairy science in the future. Constant access to personalized recommendations on what consumers should eat, whether from an artificial intelligence (**AI**)-driven tool designing a meal plan based on personal preferences or from companies that allow consumers to measure a variety of biomarkers to provide insights on health and nutrition, will become the norm in the next 25 years. The personalized nutrition, wearables, and AI-powered nutrition markets are set to grow markedly in the future. The market for AI in personalized nutrition is growing by more than 23% annually across the globe, with North America as the market leader as of 2023 (The Business Research Company, 2025). About 41% of Americans now own a smartwatch or fitness tracker, and about 4 in 10 health app users track their diet with these tools (Vaidya, 2023). Devices that can track sleep, activity, heart rate, and more are affecting the next generation of consumers, who may look to technology over their doctor for health advice, protocols, and recommendations. For example, wearables like the Fitbit Ace, designed for children 7 yr of age and older, attempt to gamify the wearable experience to help kids get more activity by providing personalized information and ways to get that activity. Technology will advance with many ways to track health—from wearables to biomarkers gathered from samples, DNA data, device data, behavioral, contextual, and environmental data, and more—to provide a real-time picture of a consumer's health status. It can be speculated that in the future, a phone, wearable, or AI advisor may collect more data and know more about a consumer's body in a day than a doctor could learn in their grandparent's lifetime, due to the amount of data that can be collected by technology on a constant basis.

Personalized nutrition companies such as InsideTracker and ZOE focus on collecting biomarkers directly from consumers' biological samples and outside data such as those from wearables, allowing the companies to assess their consumers' health in a variety of areas and then provide nutrition and lifestyle recommendations to their customers via an application. To date, InsideTracker collects blood samples from consumers, integrates their wearable (if they choose) and genetic data, and provides nutrition and lifestyle recommendations for consumers to improve in a health area of their choice (https://www.insidetracker.com/). Consumers receive "scores" for specific health areas and then choose the areas they would like to work on. ZOE collects blood and stool samples along with continuous glucose monitoring (**CGM**) data from CGM wearables and consumer-supplied nutritional data to provide personalized metabolic analysis and individualized nutrition plans (https://zoe.com/en-us). InsideTracker and ZOE are shaping the future of health recommendations by allowing consumers to bypass a doctor or nutritionist and go directly to diagnostic testing and recommendations with a company. It is important to note that in many cases, both InsideTracker and ZOE are recommending dairy products, such as fermented dairy to cheese and milk, in their personalized recommendations. In addition to startup companies such as InsideTracker and ZOE, the most influential technology companies in the world are also shaping this future where the consumer has increased oversight and insight into their health. Apple has been public about making large moves into health. The patents filed by Apple reflect a potential to provide personalized health diagnostics and recommendations. Some of their devices can double as healthcare devices. Apple watch's Atrial Fibrillation History feature gained FDA approval as a Medical Device Development Tool (FDA, 2023). Rumors of Apple's Project Mulberry, a project to bring an AI advisor to their Apple Health app and Apple watch next year, were reported on this year. Publications like Bloomberg's *Power On* newsletter and *Forbes* reported on Project Mulberry and the potential for an Apple "AI doctor" to analyze biometric data to give personalized recommendations on nutrition, lifestyle, and health (Gurman, 2025). As one can imagine, with the influence Apple has had on culture in the United States and around the world, once these features become available, they could become a baseline expectation for consumers and culture and shape new norms by 2050. Samsung (https://www.samsung.com/us/apps/samsung-health/) and Google (https://store.google.com/product/pixel_watch_2?hl=en-US) have also provided health tracking and recommendation features through their wearables and devices, and they may develop similar features.

While today, in 2025, early adopter consumers are using personalized nutrition services that gather biological samples and integrate other biological data, technology costs will be reduced by 2050, and these concepts may continue to scale as consumers experience the value. Recently, as this field has expanded and grown, multiple studies have shown how precision nutrition has led to better health outcomes (de Toro-Martín et al., 2017). These companies can conduct n of 1 "trials" in real time, allowing consumers to see the cause and effect of multiple food and lifestyle decisions. One example where this is gaining attention is through the adoption of continuous glucose monitors by everyday consumers, not just people with diabetes. One woman, a former biochemist and now social media influencer, Jesse Inchauspé, also known as the Glucose Goddess on Instagram (https://www.instagram.com/glucosegoddess/?hl=en), has formed a large community of followers, with 5.8 million followers on Instagram alone as of October 2025, by posting continuous glucose monitor results from herself or others in her community, along with nutrition and lifestyle tips. The results she posts compare different common foods, food combinations, and even food timing and how they can affect glucose spikes. She compares different types of plant-based and dairy milks, different types of dairy products with different fat levels, and even the same foods but eaten at different points in time, or during a menstrual cycle. Where it gets interesting is where 2 people eat the same food and one sees a larger glucose spike. This speaks to the gaps in knowledge around individual differences, unseen factors and environmental factors at play, and the growing ability for consumers to grasp that "one size does not fit all" when it comes to healthcare or nutrition. As more consumers can track the cause and effect of their foods through continuous measurement, they may change their daily habits with real-time insights as they notice patterns. This will affect the food industry, because consumers will be able to see the effects of each product they use. This will expose what is working and what is not for consumers. It has been rumored that Apple and Samsung are working on noninvasive blood glucose monitoring features for their wearables, with researchers exploring noninvasive CGM options (Williams, 2025). If these features come to fruition and adoption of CGM becomes even more widespread, it may force food and beverage companies to confront consumer results in real time and become more agile in the product development process. Innovation cycles may need to become quicker and more responsive, like the food and beverage industry's response to GLP-1. Danone's Oikos Fusion line, a response to GLP-1 users' specific needs, shows how the industry can respond to more specific and contextual consumer needs (DiNapoli, 2025). As consumers see the value of personalized nutrition and drive its adoption, it is important to note that the timeline, complexity, and ability of the food and beverage industry to respond is still in question. However, companies may consider learning from these concepts early on. They may consider starting the research and development process incorporating results from these technology platforms in addition to real-time data from consumers that incorporate biomarkers, preferences, and more.

How dairy currently fits into a future of precision nutrition is exciting, given that companies like ZOE and InsideTracker recommend dairy foods to their users from their data. When it comes to more agile and responsive innovation cycles, with ZOE, we see the direct pipeline to product development as ZOE launched their first kefir-based "Gut Shot" in partnership with UK retailer Marks and Spencer with 14 different bacterial strains, berries, and a kefir base (https://www.marksandspencer.com/food/the-gut-shot/p/fdp60646830). The product creation drew on ZOE's research and data from their users along with the PREDICT program study that enabled ZOE researchers to quantify and predict individual variations in postprandial responses to standardized meals in addition to gathering lifestyle information (Berry et al., 2020). ZOE choosing dairy as their first food and beverage product is a signal that the future is bright for dairy within precision nutrition systems.

As more consumers begin using personalized health and wellness technologies, their health results and behaviors may become a new platform for consumer socialization. Sharing a "sleep score" or "step count" with families and friends has been a feature for some time in wearable technology such as the Oura Ring. Consumers and families have friendly competitions over their sleep scores or step counts, motivating each other to be healthier. Precision nutrition and wearable companies have recognized this and created communities around sharing tips and tricks by creating messaging boards and platforms where people can share and seek advice. In the next 25 years, with more adoption of these technologies, and as consumers become more fluent in assessing results and "speaking the language" of their biometric data, we may see more of this. We may see a new way of interacting and socializing and a new class of influencers emerge from these platforms. Today's social media influencers generally share tips and tricks and let followers in on the intimate details of their lives, gaining trust and influence as a result. Looking out to 2050, we may find that nothing is as intimate or trustworthy as sharing the data coming directly from your body, with the biometrics and the tips and tricks that come with it. Consumers may find that they are more similar than different, in some cases, as they share and socialize around their health insights, and convene around a set of guiding principles on how to live, eat, and move. Consumers may find others like them and discover that their preferred influencer might be someone who shares their biological similarities and health goals, or has achieved the health outcome they desire. The new social media and connection in the next 25 years may be more biologically driven and centered around health optimization. This represents an opportunity for the products and solutions that generally do good for consumers in this era of tracking.

The new influencers may "look just like you"—but at a biological level. Or, they may actually "be you"—your digital twin, that is, your future AI health advisor or doctor. Digital twin technology, which involves virtual replicas of a person, project, object, or system, is set to upend the future of business and the future of healthcare and nutrition (Halamka, 2024). The ability to create a digital twin and simulate outcomes and solutions before implementing them in the real world has incredible implications for health, retail, and commerce, and all aspects of life and business. In March of 2024, Chinese president Xi Jinping announced that digital twin technology was one of "six new productive forces" in which China will lead in advancement ahead of the United States (Laubenbacher, 2024). The ability of digital twin technology to take your personal data and build a virtual version of you to simulate effects of products or recommend them cannot be underestimated when it comes to health and nutrition and will likely guide consumer decision making at a level we have not seen. For example, when eating at a restaurant, consumers could scan the menu or take a photo of a food, and have their digital twin simulate the health effects from each dish based on their biometrics that day before they decide what to order. This visual prediction technology is being developed by researchers such as those at the Artificial Intelligence Institute for Food Systems at the University of California–Davis (https://aifs.ucdavis.edu/research/projects/prediction-of-health-effects-from-food-photos).

From this technology, consumer expectations and behavior will certainly shift by 2050. A growing concept in culture and the scientific community around "food is medicine" and using food as a tool to treat or prevent disease would certainly become more prominent in the future. With new precise technological tools in this future, consumers may learn insights about their own individual health that are contrary to what they previously thought. For example, as AI, science, and technology advance and build upon each other, we are seeing certain myths "busted" and new discoveries around cures for unexplainable health conditions. For example, the cover of *Scientific American*'s June 2025 issue was titled "The Sunshine Cure" about how UV light and phototherapy can become a cure for autoimmune disease. In the article, Jacobsen (2025) notes that autoimmune diseases affect about 350 million people worldwide, and several medical studies hint that UV therapy may work for a handful of conditions such as type 1 diabetes, rheumatoid arthritis, Crohn's disease, and colitis. This is a paradigm shift from the advice most consumers are getting today, especially from their dermatologists, which is largely to block the sun's rays and wear broad-spectrum sunscreen every day (American Academy of Dermatology Association, 2025). As science advances and more is understood about sun exposure and its impact on human biology, in 25 years, consistent sun exposure may be recognized as a driver of good health. The same paradigm shifts may happen in food and beverage as these technologies scale. For example, many consumers are told to follow food elimination diets or remove dairy when they have unexplainable conditions such as autoimmune disease. When science continues to advance as AI is applied to multiple scientific fields to uncover new insights, and as consumers have the technologies to measure their health at their fingertips, we may find certain foods are not a culprit, but a solution, or that food may not play as much of a role in certain conditions as we thought.

As consumers can measure effects of foods in real time and get targeted recommendations from digital twins, AI advisors, and more, they may also come to expect more targeted outcomes from their food as a result. They may expect foods to deliver on the health outcomes they are looking for more precisely in real time, or the health areas they are looking to improve. Currently, we are seeing more customized products in the marketplace, from supplements to functional foods and beverages that claim to provide a variety of targeted health benefits from immunity to sleep, stress relief, gut health, mental cognition and focus, and more. One company, Gainful (https://www.gainful.com/), currently does this by having consumers take a survey on their websiteto outline what benefits they are seeking, and then Gainful recommends products from their portfolio, such as different types of whey protein powder ingredient blends for specific desired health outcomes. This represents an opportunity for dairy science to advance to meet the consumer where they are in 2050, in whatever targeted nutritional recommendations they are getting. Dairy milk's wide array of bioactive compounds, along with its macro- and micronutrients, make it a powerful, nutrient-dense platform for a future where health and wellness are increasingly tailored to individual needs. However, this requires an even deeper understanding of what precisely makes dairy foods beneficial. The concept of the food matrix has emerged and grown in the past decade showing how the health effects of foods are based on the structure and composition of whole foods. Although much is known about the vitamins, minerals, and macronutrient composition of dairy foods, our understanding of the other unique bioactive compounds in dairy continues to evolve. Improved accessibility of standard techniques coupled with emerging technologies will help accelerate the identification and study of bioactive compounds from dairy products. Researchers are currently seeking a fuller understanding of what is in food, by looking deeper into what makes foods healthy at a molecular level. David Wishart at the University of Alberta is one of the early pioneers who attempted this with the Milk Composition Database (https://mcdb.ca/about), which looks at metabolites in milk, in addition to the FooDB (https://foodb.ca/), which Wishart laboratory claims is "the world's largest and most comprehensive resource on food constituents, chemistry and biology." This database includes information on over 26,500 food compounds and associations including flavor, color, texture, taste, and aroma. The Rockefeller Foundation's Periodic Table of Food Initiative is preparing for this future in 2050, where nutrition is personalized and preventative, and consumers can get nutritional recommendations because molecular datasets on the composition of foods exist. Their near-term goal, as stated, is "filling the black hole of nutritional knowledge by uncovering the biomolecular composition of foods" at a global level starting with about 1,650 global foods, and this number may expand in future years (Hamilton, 2024). Private companies such as PIPA (https://pipacorp.com/) are using AI to assist private companies with the discovery of bioactives for commercialization. These efforts and the research of other scientists around the world specifically to understand the components in dairy, how they work, and how they work together, will unlock a new generation of innovation for dairy and, hopefully, health for consumers. The industry has seen great success to date in studying, commercializing, and uncovering beneficial components such as lactoferrin, milk fat globule membrane, and more. Studying and learning more about the matrix and its components will be a prerequisite for unlocking the unique value proposition that is dairy milk and dairy foods. The more funding directed toward uncovering what is in dairy and what dairy can do, the more dairy can move into 2050 successfully as a broad-spectrum health solution.

In addition to AI doctors, consumers will also get personalized product recommendations in general, beyond health and wellness, from AI agents. In addition to digital twins, the rise of agentic AI and recent programs announced by Mastercard and Visa, for example, point to a future where AI agents handle the full end-to-end process of shopping, discovering new products, providing recommendations, negotiating prices, and purchasing products or services on a consumer's behalf by learning consumers' personal behaviors and preferences (Constantino, 2025). Whereas 25 years ago it would have been unimaginable to order shoes on a cellphone from the couch to be delivered at home the next day, similar concepts may be said of agentic AI in the next 25 years, in that the product discovery process we know today may become obsolete. The connection of multiple platforms or systems that understand consumers' data will unlock the new products and services that they are looking for. They will also navigate through the noise of advertising by scanning honest reviews and price comparisons. Beyond personalized agent recommendations, consumers will of course have "of the moment" desires to participate in cultural trends or moments in the marketplace. Consumers may be able to shop their favorite TV shows or entertainment, as with Amazon's recent announcement of a "Shop the Show" feature that allows viewers to immediately shop for items that are displayed on a TV show (Ludmir, 2025). This, along with social media–enabled shopping, will provide seamless integrations of shopping in a specific cultural moment. It must be noted that the future of consumption for dairy foods relies on cultural relevance and dairy food's ability to be included in the retail concepts of the future, in addition to becoming a part of the future of personalized health and nutrition.

New advancements in AI and the ability to understand and analyze larger datasets to identify real-time personal consumer needs, preferences, and more by 2050 will push for a new infrastructure for commerce that is more direct-to-consumer or direct to their future AI agent or doctor, than ever before. It will demand a new infrastructure for research and development and innovation within the food and beverage industry in the United States in addition to a new way of marketing and commercializing goods, including dairy. Consumers not only will demand products that serve their precise needs but also satisfy their desire to participate in cultural moments of fun and enjoyment and for product features. Their agents will be able to shop for a variety of factors such as their health data, their entertainment, cultural, or social preferences, and their desire to be a more "conscious" consumer. With new technologies and advancements, consumers may develop new desires and preferences. For example, as consumers get more precise information on their health, they may be concerned not only about what is in the product but what the product is in, and how product packaging affects health. In the past couple of years, there have been multiple media reports on the health impacts of plastic and the abundance of microplastics in the water supply and environment, blood samples of consumers, and food and beverage products (Carrington, 2022).

More science and technologies will enable transparency and reveal the positives or negatives about a variety of product features, including nutrition and packaging. The dairy industry may be driven to reimagine how dairy foods are a sustainable health and wellness solution. With dairy foods being versatile, packaging will be one example where dairy foods can meet the immediate needs of consumers. Currently, there are great science projects being conducted on the ability to transform dairy byproducts, such as lactose, into biodegradable plastics, such as Ruihong Zhang's initiative at the University of California–Davis (Gautam, 2023). This showcases how dairy foods can be truly circular from farm to consumer. The dairy industry can aim to turn its waste streams into "gold," as it has historically done with whey protein (Draper, 2025). In doing so, dairy can align with the plethora of product features or criteria that consumers, or their AI agents, will look for in the future.

Although the exact timeline is unknown for when personalized nutrition, personalized AI systems, and AI agents will deeply affect and drive substantive shifts in retail and food and beverage, it will certainly reveal a new layer of complexity for infrastructure to meet the personalized needs for consumers in the future. In addition, investment demands might challenge the ability for this future to become realized quickly, especially within the dairy industry. Research and development may need to become faster and more flexible, using AI to centralize and gain knowledge about consumer health insights, dairy science, and processing innovations for speedier innovation cycles, with a more flexible pilot plant infrastructure that allows for more rapid innovation to meet consumer needs in real time. In addition to having the infrastructure in place to more quickly respond to consumer needs, uncovering what is in milk and dairy products at the molecular level is certainly required for a future in which consumers are looking for tailored health solutions. This has broader implications for the full dairy-value chain, from genetics to feed on the farm, which affect certain milk components that consumers may value in the future, to processing techniques that preserve certain bioactives, and new product formulations and formats that may be required.

Cow milk has been a versatile platform for millennia. As we are now moving closer to 2050 than to 2000, the ability of dairy to transform into a solution that can fit in to precise consumer needs is well positioned to grow over time. So much will be discovered around health and food in the next decade. To capture this value will require the efforts of the dairy science community and its funders to unlock the "magic" of the dairy matrix by discovering the unique bioactives that make dairy an incredible health food. This will reposition dairy as a high-value food uniquely capable of meeting consumer needs and supporting targeted health outcomes. It will require a greater agility and investment into research and development and the innovation process by dairy companies. It will require the ability for companies to incorporate learnings from technology and data into their research and development process to meet the precise health needs of consumers in the future, combined with continued efforts to improve product contents and packaging, upcycle waste streams for greater value, and more.

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Notes

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Nonstandard abbreviations used: AI = artificial intelligence; CGM = continuous glucose monitoring.

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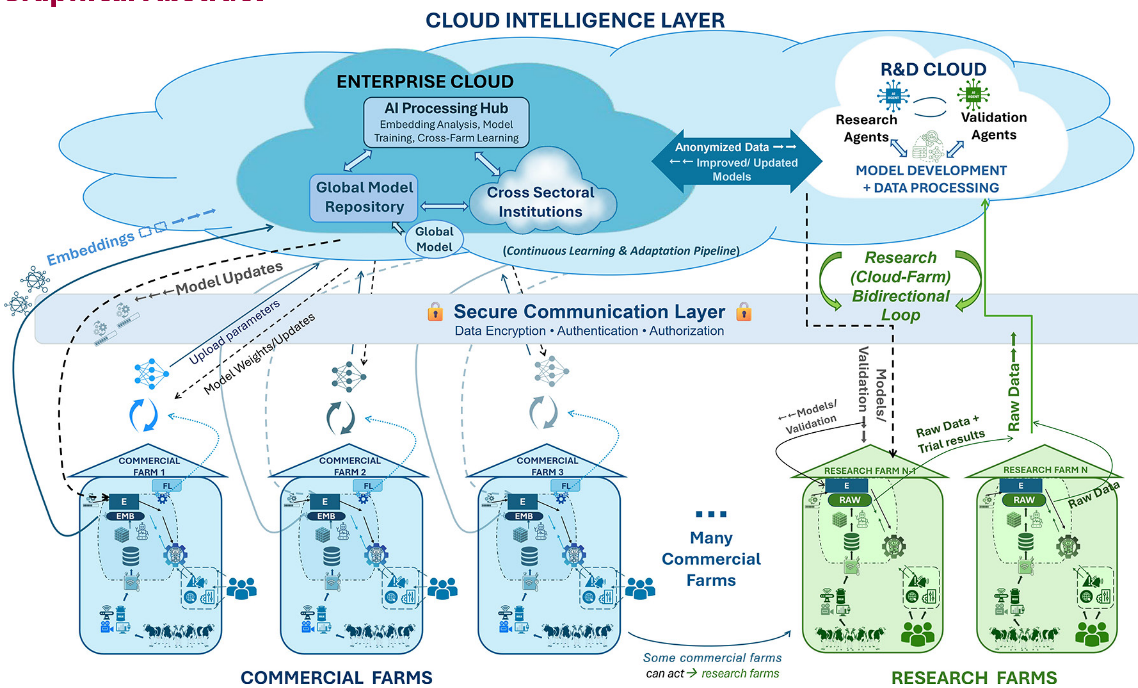
Invited Review
Animal Nutrition and Farm Systems

The future of big data and artificial intelligence on dairy farms: A proposed dairy data ecosystem

Miel Hostens,[1,2]*† Sébastien Franceschini,[1,3] Meike van Leerdam,[1] Haiyu Yang,[1] Sabina Pokharel,[1] Enhong Liu,[1] Puchun Niu,[1] Hanlu Zhang,[1] Saba Noor,[2] Kristof Hermans,[4] Matthieu Salamone,[4] and Sumit Sharma[1]*†

Graphical Abstract

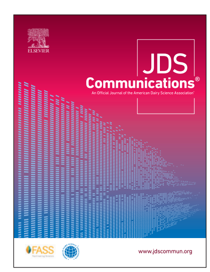


Summary

The dairy sector is operating in an environment of rapid technological change, driven by advances in big data and artificial intelligence (AI). To remain competitive and sustainable, farms should adopt intelligent, scalable, and privacy-preserving solutions. This paper presents a comprehensive ecosystem that combines multimodal AI, edge computing, and federated learning to enable real-time, data-driven decision making on farms. With emphasis on privacy, local relevance, and research integration, the framework would enable autonomous AI agents to support everyday farm decisions and long-term planning. The graphical abstract depicts a schematic representation of the proposed framework for a future dairy data ecosystem, illustrating interactions among commercial and research farms, edge devices, and the cloud intelligence layer (enterprise and research and development [R&D] clouds). It shows data and model flows, with solid arrows pointing away from farms and dashed arrows pointing toward farms. E = edge layer; FL = federated learning; RAW = raw data.

Highlights

- Presents a multimodal AI ecosystem for dairy farming's big data challenges by 2050.
- Introduces "vulnerability" and "vigilance" dimensions to the big data framework.
- Proposes a layered architecture linking farms, clouds, and research for scalable AI.
- Combines edge computing, federated learning, and autonomous AI agents in an ecosystem.
- Targeted interventions at animal and herd levels, data-driven regional-global decisions.



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The future of big data and artificial intelligence on dairy farms: A proposed dairy data ecosystem

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Abstract: The dairy sector should overcome challenges in productivity, sustainability, and data management by adopting intelligent, scalable, and privacy-preserving technological solutions. Adopting data and artificial intelligence (AI) technologies is essential to ensure efficient operations and informed decision making and to keep a competitive market advantage. This paper proposes an integrated, multimodal AI framework to support data-intensive dairy farm operations by leveraging big data principles and advancing them through AI technologies. The proposed architecture incorporates edge computing, autonomous AI agents, and federated learning to enable real-time, privacy-preserving analytics at the farm level and promote knowledge sharing and refinement through research farms and cloud collaboration. Farms collect heterogeneous data, which can be transformed into embeddings for both local inference and cloud analysis. These embeddings form the input of AI agents that support health monitoring, risk prediction, operational optimization, and decision making. Privacy is preserved by sharing only model weights or anonymized data externally. The edge layer handles time-sensitive tasks and communicates with a centralized enterprise cloud hosting global models and distributing updates. A research and development cloud linked to research farms ensures model testing and validation. The entire system is orchestrated by autonomous AI agents that manage data, choose models, and interact with stakeholders, and human oversight ensures safe decisions, as illustrated in the practical use case of mastitis management. This architecture could support data integrity, scalability, and real-time personalization, along with opening up space for partnerships between farms, research institutions, and regulatory bodies to promote secure, cross-sector innovation.

Since the early 21st century, the dairy industry has been characterized by increasing integration of big data, artificial intelligence (**AI**), robotics, internet of things (**IoT**), and technologically advanced equipment (Gehlot et al., 2022). Predictive models for precision livestock farming, built on advances in machine learning and deep learning (Cockburn, 2020; Mahmud et al., 2021), range from yield forecasting using historical data (Salamone et al., 2022), behavioral prediction with sensor data (Liseune et al., 2021), health monitoring (van Leerdam et al., 2024), computer vision (Borges Oliveira et al., 2021), and milk mid-infrared spectrometry for herd management (Franceschini et al., 2025). Such applications illustrate how AI-driven tools, which are computational models ranging from simple statistical regressions to advanced machine learning and deep learning methods, can enhance decision-making and optimize production efficiency. However, widespread field applications remain limited, and although the sector generates terabytes of operational data daily, its value is underutilized due to poor integration of monitoring systems (Palma et al., 2025). This challenge ties into the foundational 5 key dimensions of big data; volume, velocity, variety, veracity, and value (Hermans et al., 2018; Nguyen, 2018) which will stay relevant, though their dynamics will evolve. In this evolving landscape, new challenges arise. Two closely connected dimensions that are becoming increasingly important but are rarely or never mentioned in big data discussions and publications are referred to as "vulnerability" and "vigilance." These emerge as critical additional challenges, highlighting the need for resilient data infrastructure and proactive protection of integrity and privacy. Because AI-driven platforms collect, interpret, and act on large volumes of data transmitted to cloud services or external providers, addressing both vulnerability and vigilance is essential for securing data, ensuring ethical management, and building trust in future-oriented, data-driven systems.

Although many innovative and traditional solutions exist across fields from computer science and engineering to biomedical sciences, the dairy industry has yet to integrate them into a practical data framework. This is why a novel framework is proposed in this paper, combining multiple technologies to provide dairy-specific solutions and maximize data value. The paper is intended for researchers, specialists, farm technology developers, and practitioners engaged with data-driven systems in dairy farming, highlighting opportunities for the application of various concepts rather than detailing a single implementation. It is assumed that readers have basic familiarity with data science; when specialized terms are introduced, concise explanations are provided. First, key concepts of some solutions relatively new to the dairy sector will be described to provide a comprehensive understanding of their potential. These concepts are then integrated into the proposed

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framework, designed to support the broader dairy ecosystem and set the stage for the rest of the paper.

Dairy farms produce vast, diverse datasets, ranging from milk yield and animal behavior to genomics, feed, environment, soil, and finances, supplemented by external data streams like weather and market data. Their volume and velocity demand scalable storage and near-real-time processing, with integration across sources remaining the major challenge (Cabrera and Fadul-Pacheco, 2021). To address part of these challenges, multimodal AI emerges as a promising solution tackling data heterogeneity. Multimodal AI refers to AI systems designed to process and integrate the input of different data types (e.g., structured data such as sensor readings or tabular information, as well as unstructured data such as text, images, audio, and video) into a single cohesive model (Fuchs, 2023; Arjunan, 2024). This solution captures cross-modal relationships and achieves a more complete, context-aware understanding of input data, surpassing the capabilities of unimodal systems (Ruan, 2024).

As data exceeds local storage, cloud solutions become essential, but sharing sensitive farm information outside the farm raises privacy concerns. Farmers worry that unauthorized access to data (such as yields, finances, or land use) could lead to cyberattacks or misuse, threatening livelihoods and personal privacy (Kaur et al., 2022), a concern that is likely to grow. This is where latent representations captured through dimensionality reduction like embeddings, stored as tensors, can be used. A tensor is a multidimensional array that represents complex data such as images, videos, and time-series (Cichocki, 2018). An embedding is a specific tensor that maps high-dimensional data into a compact, lower-dimensional vector space capturing relationships between data points for efficient storage and processing (Xu, 2021). Typically, data will be first converted into tensors for computation, from which embeddings are learned to create meaningful representations used as input in predictive models (Liseune et al., 2020). Although it is not their primary purpose, embeddings also help to preserve privacy during data sharing by transforming raw sensitive data into an abstract form where the original information can be obscured, making it difficult to reconstruct sensitive details without access to the model that was used to create the embeddings. This allows downstream models to work with the embeddings without ever accessing the raw data, ensuring privacy is maintained. Furthermore, this method is compatible with collaborative research and federated analytics across farms. It is also supported by the concept of federated learning, which is a machine learning approach for decentralized model training, where models train on local data at various sites (e.g., farms) and only aggregated updates are shared with a central server, ensuring privacy and data security without sharing raw data (Dembani et al., 2025).

Another important concept is cloud computing. This paradigm offers an effective solution to train universal global models by integrating data or embeddings from different sources (i.e., farms) and providing the computational power and storage needed for large-scale data analysis (Wang et al., 2024). Through this, farms can offload heavy data processing, model training, and long-term storage to remote data centers, enabling centralized, scalable farm data management. However, cloud computing relies on consistent network connectivity, and for remote farms with unreliable internet, critical alerts such as calving or health warnings may be delayed, jeopardizing time-sensitive interventions. Also, small and medium-sized farms often lack computing power or standardized platforms to manage big data with AI, impeding scalability and adoption of precision approaches (Lokhorst et al., 2019). Edge computing mitigates this by performing storage and computation closer to data sources. This distributed paradigm brings computation and data storage near generation points (e.g., IoT devices or sensors), reducing latency, improving response times, and optimizing bandwidth by processing data locally rather than relying solely on centralized servers (Shi et al., 2016). Edge devices can run lightweight AI models, preprocess data on-site, and limit cloud uploads for tasks such as model training and storage. Additionally, combining edge computing with privacy-preserving embeddings ensures fast, secure processing while protecting sensitive data. Local nodes convert raw sensor inputs into embeddings, perform inference locally, and share only anonymized data with central servers (Žalik and Žalik, 2023). Although edge computing excels in real-time processing, it cannot handle complex tasks such as global model training or long-term storage, which cloud computing enables. Therefore, an integrated edge-cloud framework can be necessary to achieve both real-time performance and scalable, secure data management.

To further enhance on-farm intelligence and reduce manual oversight, autonomous agents can be integrated into this edge-cloud framework. These software entities perceive their environment, make decisions, and act toward specific goals without continuous human intervention. They use techniques such as planning, reinforcement learning, and decision making under uncertainty (Acharya et al., 2025) to optimize outcomes and improve over time by learning from farm data. These agents handle complex, data-driven tasks involving scientific modeling, statistical analysis, and algorithmic computation, which are critical for precision agriculture but fall outside traditional farming skills, and thus typically cannot be performed by farmers. They reduce cognitive load on farmers, researchers, and administrators by translating complex analytics into clear, contextual recommendations tailored to farm size, location, and goals.

To support such AI systems, dedicated research and development (**R&D**) infrastructure is essential. Pilot testing on research farms with advanced instruments for new data generation provides critical feedback to validate models, test technologies, and assess adaptability before wider deployment. These living labs collect high-quality data under real conditions, refining multimodal models, embeddings, edge computing, and data management. Although commercial farms may lack such setups, insights from research farms serve to guide farm agents in developing evidence-based practical solutions by integrating research findings with farm-specific data streams.

By bringing these elements together, the evolving challenges of future dairy farming can be addressed through an approach that incorporates the multitude of V's (volume, velocity, variety, veracity, value, and the newly introduced vulnerability and vigilance). Integrating advanced big data and AI into farm management, a framework is proposed as an intelligent, privacy-preserving system designed to operate within an IoT-enabled, adaptive, and sustainable farm ecosystem, aiming to establish a forward-looking digital dairy ecosystem that enhances resilience, efficiency, and sustainability. The design is conceptualized as a multilayered system across scales, including individual cows, herds, and the industry level, consisting of interconnected components that collect, process, and share data and models, enabling farms to leverage AI while maintaining security and confidentiality. At its core, it combines edge computing, multimodal data, autonomous agentic systems, and a secure communication layer (incorporating data encryption, authentication, and authorization), along with a dedicated R&D environment for continuous performance improvement and an efficient data transfer subsystem (see the graphical abstract). It optionally incorporates federated learning, enabling farms to collaboratively train models while also preserving data privacy and delivering locally optimized outcomes. The overall architecture and data flow between the system components are illustrated in the graphical abstract and the detailed farm view in Figure 1 (refer to https://github.com/Bovi-analytics/Hostens-et-al-2025/blob/main/Model_FrameworFinalFull.jpg for the integrated version).

The framework contains 2 main components: the farm (commercial and research) and cloud (cloud intelligence layer), with the cloud comprising the enterprise cloud level and the R&D cloud level. At the farm level, multimodal data are collected and processed, including farm management data, sensor data, feed and robot data, and video streams. Here, the edge layer and main system form the foundation for the tasks. These sources gather raw data, which are processed locally using edge computing. Encoders, coordinated by autonomous agents, transform raw inputs into structured numerical forms (tensors) and further into semantic representations (embeddings) that capture relational or contextual meaning (Figure 2). Once generated locally, farm embeddings are securely transmitted to an enterprise cloud environment for further refinement and analysis without exposing any raw farm data. As such, farms could participate in a federated learning network where local edge models train on farm-specific data and only model gradients or weights are shared with the enterprise cloud for aggregation into a global model. This mix of anonymized embeddings for targeted analytics and shared model updates allows farms to benefit from collective intelligence while still preserving privacy. The edge layer supports this architecture by managing local training, ensuring cloud communication, and continuously adapting its output to evolving global insights. It also receives updated models and alerts from the enterprise cloud to optimize operations such as predicting milk production, monitoring animal health, and detecting anomalies or suboptimal conditions. The actual monitoring of farm activities, especially those requiring immediate responses, is primarily carried out by autonomous AI agents running on edge devices, which analyze data in real time, generate embeddings, and trigger alerts or reports. Meanwhile, the enterprise cloud focuses on aggregating data across farms, refining global models and identifying long-term trends and patterns. When necessary, generative AI interface agents can provide adaptive alerts or instructions in local languages or dialects via voice or visual cues, improving decision making and accessibility. Continuous monitoring and response are thus enabled by edge AI agents, whereas cloud-level agents support strategic coordination, model improvement, and global intelligence across the farm network. The system within farms is built to support decisions, with the main system operating under human (farmers and consultants) supervision. The human-in-the-loop setup ensures that everything follows the right protocols, and the final decisions, such as treatments, interventions, or changes on the farm, are made by the farmer or consultant based on the situation and their experience.

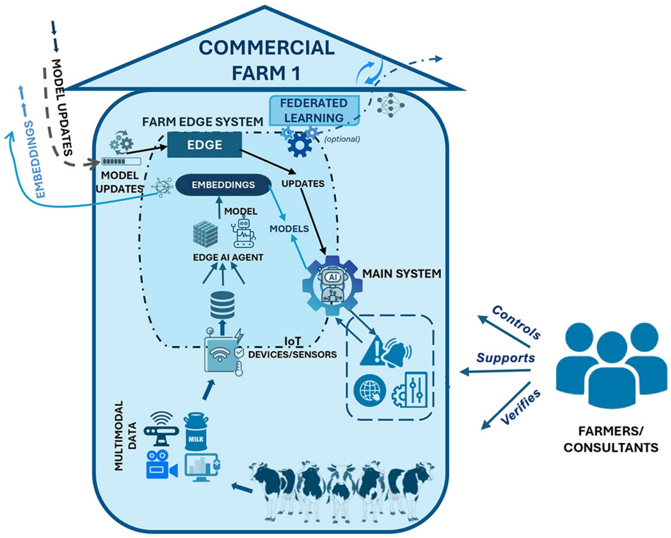

Figure 1. Detailed view of a commercial farm AI system corresponding to the graphical abstract ecosystem. Collected multimodal herd data are processed locally by a farm edge (edge AI agent), which generates embeddings and model updates (optional federated learning) that are transferred to the cloud. The main AI system aggregates updates, issues decisions, and interfaces with farmers and consultants who verify, control, and provide feedback.

The enterprise cloud level serves as the central hub of intelligence, receiving embeddings from commercial farms and pushing updated models back to ensure continuous adaptation and optimization. Within this layer, several key components interact to support the process, including a global model's repository for storage and distribution, an AI processing hub for embedding analysis, model training, and cross-farm learning, and access for cross-sector institutions for secure knowledge exchange and collaboration. This layer is also directly connected to the R&D cloud level, from which it receives updated models for deployment to farms. In this way, this level integrates diverse embeddings into advanced analytics, connects with institutions for access to global findings (e.g., cross-regional impacts and emerging risks), and acts as a key information source to support R&D decisions, all while ensuring data privacy at every stage. Although autonomous AI agents on edge devices perform real-time monitoring and detect issues such as animal health risks or operational inefficiencies locally to preserve privacy, autonomous cloud agents analyze the resulting embeddings without knowing their farm of origin. These cloud agents can detect broader population-level anomalies and trends, such as disease outbreaks, and generate tailored, data-driven responses. They operate without access to raw data or farm identities, adhering to a private learning paradigm that enables farms to receive personalized insights while keeping their data confidential. If anomalies are found, agentic AI can intervene through a generative AI layer to deliver customized action plans for farmers, industry stakeholders, and policymakers.

Another tailored component within the framework is a targeted connection to research farms, which constitute the R&D cloud, that are tightly integrated into the framework and serve as a testbed for advanced model development and validation. In contrast to commercial farms, research farms could opt to share raw data directly.

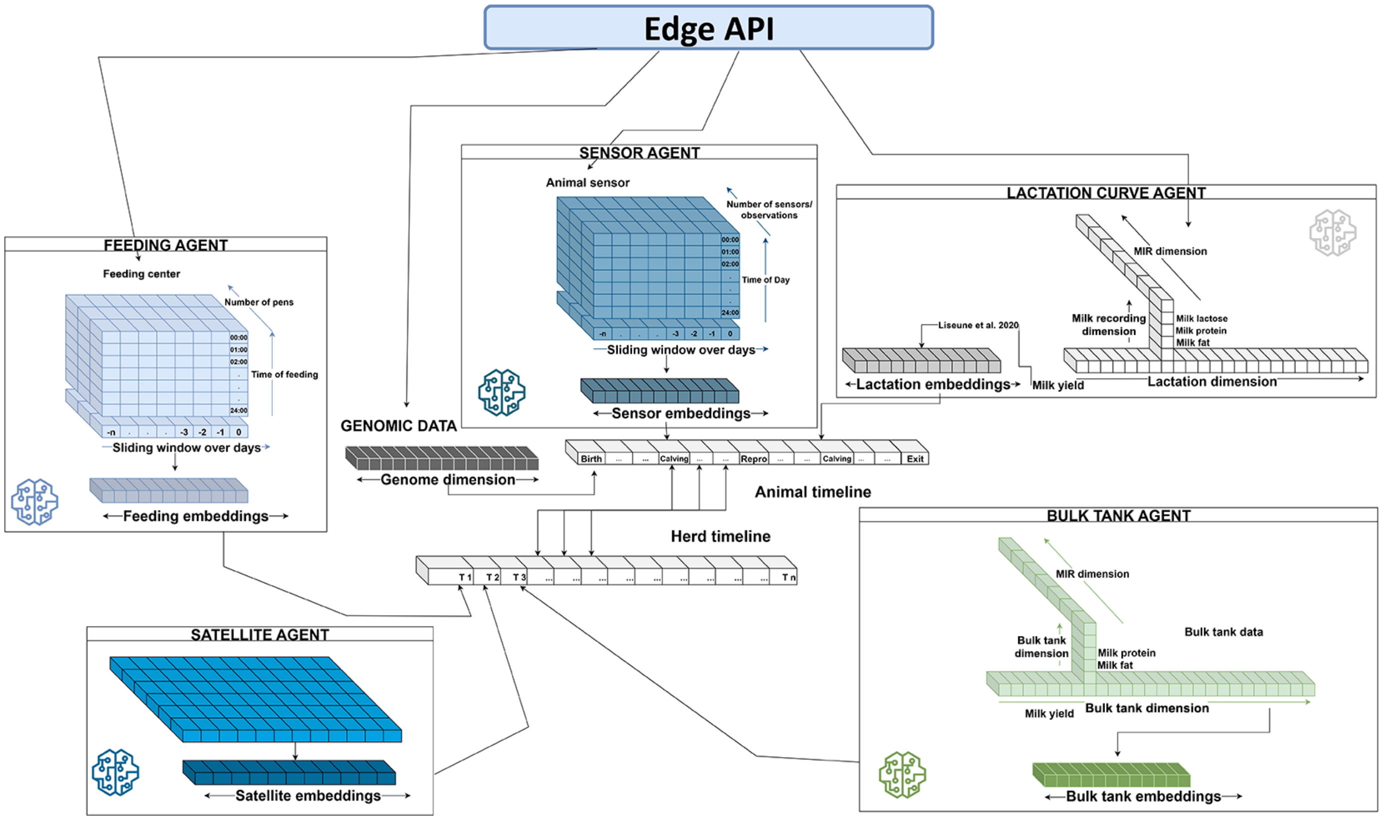

Figure 2. Examples of tensor representations and embeddings in dairy farm data. Multidimensional tensors from milk yield, activity, environment, and genomics are processed locally via standardized application programming interfaces (API) to generate privacy-preserving embeddings. MIR = mid-infrared spectroscopy; Repro = reproduction.

Researchers as well as autonomous agents in this environment could experiment, refine models, and validate their performance under controlled experimental conditions. This process is critical for generating high-quality operational models (i.e., models used to derive insights and support decision making in farming operations) that will go through the enterprise clouds for dissemination to commercial farms, ensuring that only validated cutting-edge innovations reach the industry. It is well established that benchmarking data and continuous refinement of detection models are crucial to optimizing system performance and relevance in a constantly evolving environment. Although dedicated research farms are assumed to exist, some commercial farms can also share raw data through the cloud for benchmarking and deeper analysis, enabling them to contribute to research efforts and improve embedding generation or discover new insights. These commercial farms may also continue to serve this dual role in the future, meaning they can provide raw data to the research cloud whenever embedding generation needs improvement or new insights are discovered, effectively functioning as research farms when they choose to do so. Such flexibility reflects the evolving landscape where commercial and research farms are not strictly separate entities.

To support ethical scaling and advancement, the enterprise cloud facilitates secure exchange of insights with cross-sector institutions involved in research, innovation, and training. These entities receive only insights derived from embeddings, or, when explicitly approved, the raw data, allowing them to conduct training, research, and collaborative studies without accessing raw sensitive farm data. They contribute their own findings, tools, and updates, feeding emerging research back to the enterprise level. Enterprise AI agents can also be triggered by these insights and trends to initiate actions in the R&D cloud, such as adapting models, suggesting experiments, or flagging risks or opportunities. This arrangement enhances transparency, scientific rigor, and mutual benefit across the ecosystem, driving industry-wide progress in big data and AI applications without extensive data transfer authorization protocols, which are unseen in our industry today.

Sustainability will be embedded into every layer of technological development, including prioritizing energy-efficient machine learning models, edge computing to reduce reliance on centralized data centers, and hosting systems on renewable-powered, green-certified cloud platforms. Data minimization strategies will be applied to reduce storage and energy demands. In addition, acting with greater speed and precision through intelligent decision support systems can help farmers to reduce waste, use resources more efficiently, and lower environmental impacts. Co-developing tools with sustainability experts will ensure that environmental impacts are considered early, and over time, these technologies will inevitably be governed by evolving climate policies and standards.

Maintenance of dairy herd health is a challenge experienced in many dairy farming contexts. In technology-forward farming systems, mastitis monitoring can serve as a practical use case to show how the framework translates data into daily management decisions. Imagine a dairy farm where cows are monitored continuously through sensors, milk meters, and cameras, alongside environmental, health, and farm management data. This information is processed locally via edge computing, transformed into embeddings that represent each cow's physiological and behavioral patterns and the context it lives in, and fed into an on-farm mastitis prediction model. When the model detects a high-risk case, it generates an alert with evidence such as confidence scores, the features driving the decision (e.g., milk conductivity rise, activity drop), and a suggested next step. The farmer or consultant reviews the alert, inspects the cow, and makes the final treatment choice; confirmed case or false alarm provides feedback to the model (called reinforcement learning). Agents supporting this process use generative AI and large language models to deliver farmer-friendly advice in local dialects, for instance by answering the question "Which cows are most at risk for mastitis today, and what should I do?" The agent analyzes farm data, provides individual risk scores, prioritizes cases, and suggests actions based on farm-defined protocols. Importantly, the system is decision-support, not decision-replacement: areas that often involve complex clinical, ethical, or regulatory considerations such as treatment decisions that involve antimicrobial use, reproductive interventions, pain management, culling, or euthanasia remain with humans (farmers, consultants, and veterinarians) and are supported by built-in safeguard mechanisms to ensure responsible and transparent use of AI.

Once a mastitis case is confirmed or rejected, the outcome is used to update the prediction model locally through federated learning. The updated model weights through federated learning and embeddings through edge are sent to the cloud, where enterprise agents track cross-farm or regionally or globally concerning trends (e.g., rising *Escherichia coli* incidence) and can coordinate with veterinary and research partners. In parallel, research and validation agents analyze the pattern using high-resolution data from research farms with gold-standard reference data to validate and refine models, which are redistributed back to production farms, closing the loop between detection and scientific model development. As models are continuously updated, they adapt to factors such as herd size, local disease pressure, climate, and infrastructure, making the framework configurable for diverse production contexts. On large, well-instrumented US farms (e.g., 10,000 cows), the full-stack approach (edge inference, near-real-time embeddings, cloud trend monitoring, and continuous research validation) supports sophisticated, farm-specific tuning. In low-resource settings (e.g., a 100-cow smallholder system in Malawi), the same framework adapts by simplifying components: lower-bandwidth edge models, prioritized low-cost sensors, and emphasis on low-cost interventions. In such contexts, even common smartphones or lightweight local devices can function as edge units, enabling on-farm inference and data handling without reliance on expensive infrastructure.

The proposed framework may face some challenges and limitations. There may be initial reluctance among farmers or farms to share data due to concerns about privacy, misuse, and the potential loss of competitive advantage, which can affect early adoption. Additionally, the computational load and energy demand of large-scale cloud-based analytics raise economic and environmental concerns. Implementing and maintaining such systems also requires technical expertise and skilled personnel, which might not be readily available in all agricultural settings. Ethical considerations are also important; our framework includes human oversight for safety-sensitive decisions such as antibiotic use, but this must be continuously monitored and refined. Despite these challenges, trends in other sectors show that participation tends to grow once the benefits become clear and proper safeguards are in place. Over time, improvements in energy efficiency, the shift to greener cloud infrastructure, and the trend toward smaller, faster, and more affordable devices are likely to reduce many of these barriers. As interfaces become easier to use and automation takes over routine tasks, daily management becomes less demanding. As benefits become clear, farmers and stakeholders can transition to hybrid setups involving periodic cloud synchronization for benchmarking and coordination, eventually moving toward full-stack integration. It is also recognizable that the ideas in the framework can be costly or exclusionary if applied right away. Common barriers such as limited capital, poor connectivity, or lack of technical expertise can be addressed through future cooperative purchasing, extension-led support, vendor-managed deployment models, or public-private and grant-based support for early adoption. Cost-control measures such as data-trust models, subscription or tiered pricing, and shared infrastructure can also help. Over time, ongoing innovation, economies of scale, and improved user accessibility are expected to drive costs down. Although current limitations are real, the direction of technological progress and the evolving mindset within the farming community suggest that practical and sustainable adoption of such data-driven systems is not only possible, but increasingly likely.

In this way, the concept lays a foundation for the future of dairy data operations. Although the future remains inherently dynamic and ever-changing, current trends and rapid advances suggest that such a dairy data ecosystem could guide how farms might operate by 2050. The tools may not develop exactly as described, but the direction is clear: big data and AI can make farming smarter, more efficient, and more sustainable. Integrating technologies such as multimodal AI, edge computing, federated learning, and cloud infrastructure points to a vision of future dairy supported by autonomous AI agents. Over time, these systems could lead to the development of digital twins, which are high-fidelity virtual models that replicate physical farms in near real-time, running predictive models, testing intervention strategies, and supporting long-term planning without disrupting real operations.

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Notes

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Nonstandard abbreviations used: AI = artificial intelligence; API = application programming interface; IoT = internet of things; MIR = mid-infrared spectroscopy; R&D = research and development; Repro = reproduction.

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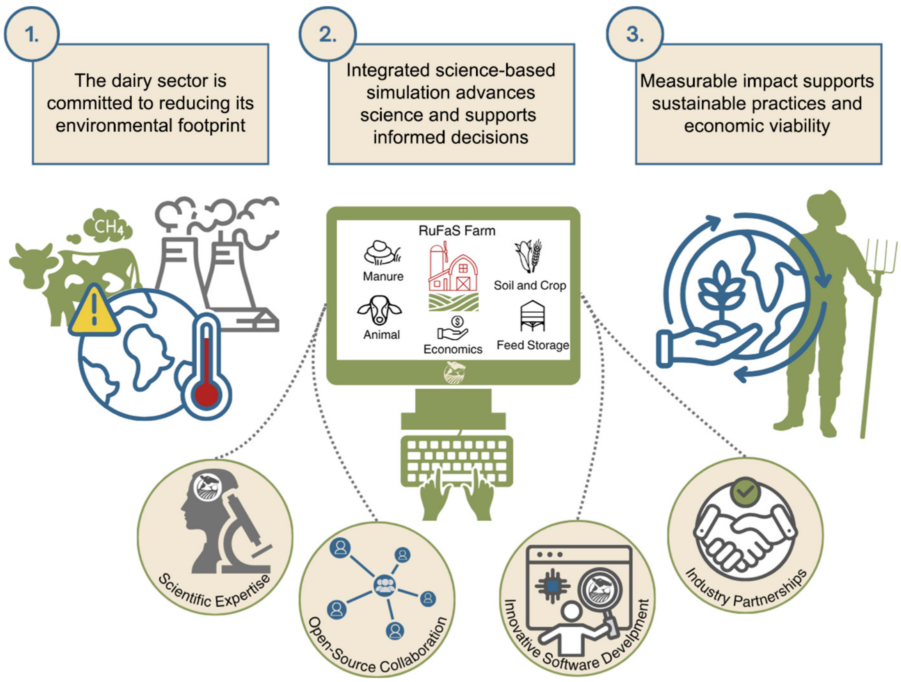
Invited Review
Animal Nutrition and Farm Systems

The Ruminant Farm Systems (RuFaS) model is a platform to support future research and actions for sustainable dairy farming

K. F. Reed,[1]* J. M. Tricarico,[2] S. HekmatiAthar,[3] J. S. Waddell,[2] D. A. Andreen,[4] K. R. Briggs,[5] A. Liu,[4] N. D. Tomlinson,[4] J. Adamchick,[6] V. E. Cabrera,[3] H. Hu,[4] Y. Gong,[3] G. M. Graef,[6] M. R. Villalobos-Barquero,[4] J. P. Oliver,[7] D. V. Nydam,[6] N. Ayache,[8] and L. McClintock[2]

Graphical Abstract

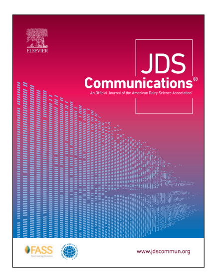


Summary

Whole-farm models like the Ruminant Farm Systems (RuFaS) model integrate information to support advances in sustainable dairy research and production. The open-source platform, modern software development, and detailed documentation in the RuFaS modeling environment are designed to foster collaboration and innovation.

Highlights

- Integrates animal, manure, crop, and feed processes in an open-source, modular platform.
- Supports assessment of trade-offs and synergies in sustainability strategies.
- Identifies research gaps by revealing downstream effects and system interactions.
- Accelerates scientific innovation and informs industry and policy decisions.



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The list of standard abbreviations for JDSC is available at adsa.org/jdsc-abbreviations-25. Nonstandard abbreviations are available in the Notes.

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Abstract: The Ruminant Farm Systems (RuFaS) model is an open-source, modular, whole-farm simulation platform designed to support interdisciplinary research, innovation, and decision making in sustainable dairy production. This review outlines RuFaS structure, functionality, current applications, and potential for further development. Through integration of biophysical modules for animal, manure, soil and crop, and feed storage systems, RuFaS enables comprehensive evaluation of management strategies, environmental interventions, and productivity outcomes in a whole-farm context. The RuFaS model facilitates hypothesis testing, multi-objective analysis, scenario evaluation, and identification of research gaps by simulating interactions and trade-offs across biological, environmental, and management domains. The model's current applications include its integration into the Farmers Assuring Responsible Management Environmental Stewardship program for GHG accounting and its use in evaluating innovations in nutrition, breeding, and manure management technologies. Its modular architecture supports rapid prototyping, modeling at different scales, and uncertainty analysis, making it adaptable to diverse research questions and stakeholder needs. Finally, it highlights the critical role its open-source foundation has for promoting transparency, reproducibility, and collaborative development across disciplines. Its transparent development process, hosted on GitHub under a GPLv3 license, invites contributions from across disciplines and institutions. Scientists are encouraged to explore RuFaS as a tool for advancing their own research, contributing to model development, and engaging in a shared effort to improve the sustainability of dairy systems.

Dairy farms are dynamic, complex systems in which changes to one component—such as feed management, herd health, or manure handling—can trigger cascading effects across the entire operation. When research or management decisions are made in isolation, these interdependencies are often overlooked. Whole-farm systems models help reveal these interactions, enabling more informed decisions about resource use, environmental impacts, and economic trade-offs that would otherwise remain invisible in compartmentalized analyses. Agricultural systems models have been in development for decades (Jones et al., 2017a) and there are several existing models capable of representing the whole dairy farm for the purposes of estimating GHG emissions (Rotz, 2018) and other environmental effects. These models produce informative analyses that synthesize current understanding of the physical, management and weather factors driving dairy farm production and environmental impacts (e.g., Veltman et al., 2018; Díaz de Otálora et al., 2024; Godber et al., 2025). The advancement and effects of these models are limited by the state of science and the rate with which they are able to incorporate new scientific knowledge.

Technological advances in computing power, programming languages, and web-based collaboration platforms, create opportunities to build on the intellectual foundation of the existing models while overcoming some of the structural and conceptual limitations highlighted by Antle et al. (2017), Janssen et al. (2017), and Kebreab et al. (2019), such as the lack of integration between parts of the farm, limited or restricted sets of management options, and intractable code bases that restrict the scope and scale of their application and effect. The Ruminant Farm Systems (RuFaS) modeling platform has been in development since 2018 and is designed to meet the growing demand among scientists and dairy sector stakeholders for next-generation, integrative, whole-farm models that facilitate improved and accelerated research to inform coordinated strategies that address sustainability challenges across the dairy supply chain (Table 1).

In this mini-review, we describe the significance of systems models for dairy research and industry decision making; summarize the current functionality, applications, and future directions of RuFaS; and highlight the benefits of open-source model development and RuFaS as a platform for open, transdisciplinary, scientific collaboration to advance dairy research and strengthen sustainable dairy production.

Most agricultural research focuses on single system components because rigorous and replicable results necessitate narrowly defined questions. However, the effects of most research findings

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Table 1. Peer-reviewed publications and select proceedings and abstracts reporting development and application of the Ruminant Farm Systems Model

Reference	Publication type	Summary
RuFaS (2025b)	RuFaS documentation	Scientific documentation of the RuFaS Animal Module.
Hu et al. (2025a)	Peer-reviewed manuscript	Illustration of model-based systems engineering application in development of the RuFaS model and case study of the interactions of dairy cow diet, climate, and manure management on greenhouse gas emissions.
Hu et al. (2025b)	Abstract	Preliminary study to evaluate RuFaS barn-floor NH_3 emission predictions.
Ayache et al. (2025)	Abstract	Summary of methods used to test and integrate RuFaS as the scientific model for FARM-ES.
Gong et al. (2025)	Peer-reviewed manuscript	Development of the method to adjust parity-specific lactation curve parameters in RuFaS to match whole-herd annual milk production.
Weigel et al. (2025)	Peer-reviewed manuscript	Application of the RuFaS model to assess the environmental impacts of genetic selection of dairy cattle.
Reed et al. (2024)	Conference paper	Summary of lessons learned from pilot testing RuFaS on 33 farms for integration with the FARM-ES system.
Li et al. (2023)	Peer-reviewed manuscript	Description and application of the Animal Module to evaluate the effects of reproduction programs on herd level outcomes and profitability.
Gong et al. (2023)	Abstract	Development and preliminary application of RuFaS methods for simulating genetic inheritance.
Li et al. (2022)	Peer-reviewed manuscript	Development of a database of lactation curve parameters for use in the RuFaS model.
Reed (2022)	Conference paper	Application of the RuFaS model to assess the environmental benefits of reproductive efficiency.
Li et al. (2022)	Peer-reviewed manuscript	Development and testing of methods for least-cost diet formulation methods used in RuFaS.
Hansen et al. (2021)	Peer-reviewed manuscript	Initial description and application of the RuFaS Animal Module to quantify the environmental benefits of improved feed efficiency.
Hansen et al. (2020)	Abstract	Development of the methods for maintaining a mass balance of phosphorus within the Animal Module.
Kebreab et al. (2019)	Peer-reviewed manuscript	Review of existing dairy systems models and motivation for a new approach to whole-farm models.

extend beyond the defined scope of inquiry, and in the context of dairy production, it is difficult to predict and quantify how these effects will percolate throughout the farm without an integrated systems model. The holistic and quantitative outputs of farm-scale models can therefore provide useful feedback at multiple points along the research and development pipeline by helping to identify gaps in knowledge and systems-level trade-offs, providing a virtual platform for hypothesis testing and optimization at different scales and establishing priorities for future work (Figure 1).

Whole-farm, integrated assessments of proposed sustainability interventions are needed to quantify their total and relative effects and identify their trade-offs beyond the scales that can be achieved through empirical research. For example, the evaluation of best management practices by Veltman et al. (2018) using the Integrated Farm Systems Model (**IFSM**; Rotz et al., 2018) could be used to prioritize future research and investment in GHG mitigation programs. This integrated and quantitative assessment identifies feed and manure mitigation strategies as higher priority for research and management intervention to achieve GHG mitigation on dairy farms because they account for more than 90% of the total predicted reduction. Conversely, if the objective is to reduce phosphorus runoff rather than GHG emissions, their analysis points to a focus on field mitigation strategies like no-till and cover cropping. This example illustrates a critical advantage of whole-farm models for multi-objective analysis. By simulating trade-offs and synergies among diverse sustainability goals like GHG mitigation, nutrient management, and productivity, systems models enable researchers and decision makers to evaluate interventions in relation to a broader set of farm and environmental outcomes.

Whole-farm models also provide a low-cost way to scale potential outcomes, develop and test hypotheses, and identify future research needs from preliminary results of novel technologies. For example, feed additives to reduce enteric methane (CH_4) have been widely studied in lactating cows in confined systems but their effects on young stock, and downstream effects on manure nutrient composition, manure and soil emissions, and crop productivity are largely unknown (del Prado et al., 2025). These knowledge gaps limit the ability to evaluate the effects of interventions for the entire system and constrain efforts to optimize across multiple sustainability objectives, thus emerging as key areas for future research.

Simulating manure excretion and composition across diets and life stages also demonstrates the strategic role of systems models in uncovering research gaps. During RuFaS development, we found wide variation in existing manure excretion prediction methods, especially for calves and heifers, where estimates often rely on BW and intake alone rather than diet composition, thus increasing uncertainty. These limitations, although affecting a small share of emissions, reduce confidence in downstream predictions of water quality and GHG outcomes, emphasizing the need for targeted research. Because integrated analyses that account for downstream effects are key elements of multi-objective sustainability assessments, this underscores the strategic value of integrated systems models not only in identifying research gaps but also in enabling more accurate and precise evaluation of sustainability interventions and in promoting interdisciplinary science.

The advantages of farm systems models for industry and policy mirror the same qualities that make them essential for sustainable dairy research. In particular, the integration of data and processes across the whole farm is a prerequisite for informing decisions related to strategic planning and investment. The ability to conduct benchmarking and comparative analyses of sustainability outcomes at the level of the farm, supply chain, or political region relies on accurate and precise predictions that include both immediate and downstream effects of system changes. Although whole-farm models like RuFaS, IFSM, and COMET-Farm (Paustian et al., 2017; COMET-Farm, 2025) are not designed to directly generate life cycle assessment, inventory, or footprinting results, they play a critical role in supporting those applications by providing detailed,

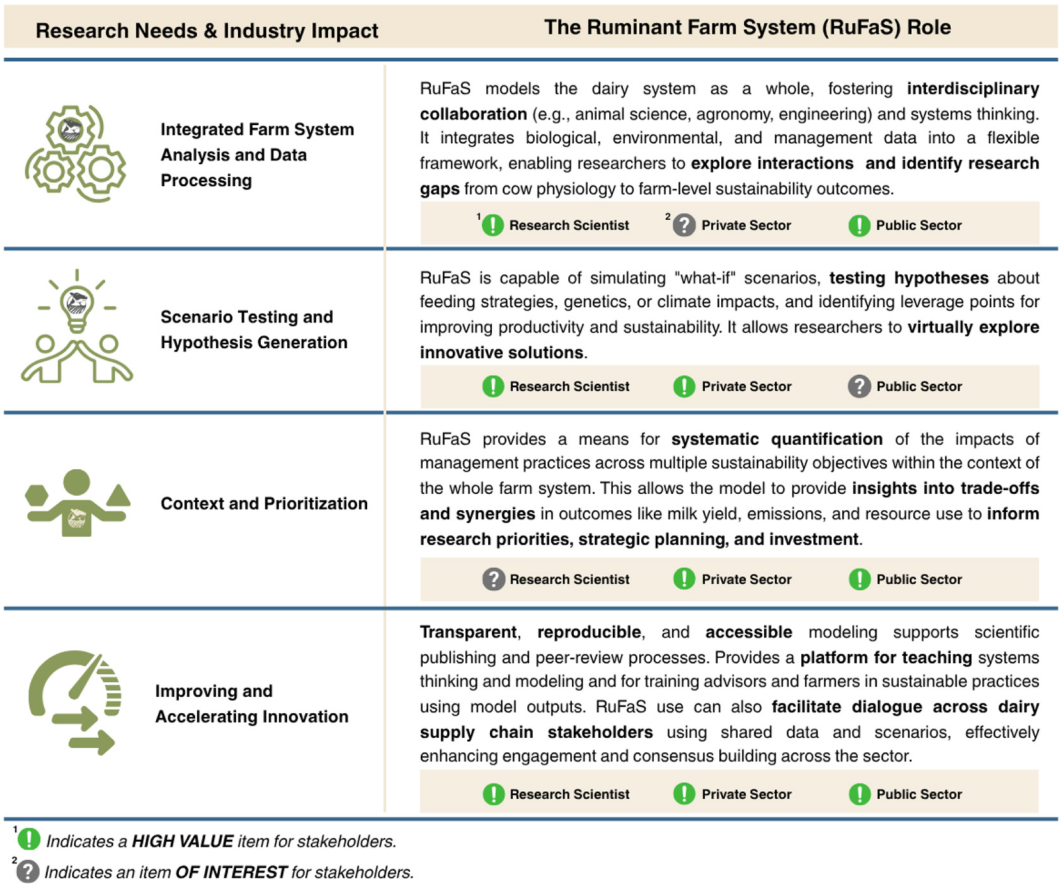

Figure 1. Illustration of research and dairy industry needs for whole-farm systems models, the ways the RuFaS model can meet those needs, and the key stakeholders who will benefit.

process-based outputs. These outputs must be further synthesized through additional methods, models, or summary analyses to produce the environmental indicators required for most reporting use cases. For example, RuFaS underpins the Farmers Assuring Responsible Management (**FARM**) Environmental Stewardship (**FARM-ES**) program for GHG accounting adopted by processors and cooperatives that make up 80% of the US milk supply. The farm-level outputs from RuFaS provide the majority of inputs for FARM-ES to generate cradle-to-farmgate emissions footprint values for aggregated supply chain reporting by dairy cooperatives, processors, and downstream customers. With the addition of the upcoming Economic Analysis Package, RuFaS integration with FARM-ES will increase the dairy sector's ability to support farmers and cooperatives on their path toward the environmental goals set for 2050 by providing insights into financial sustainability.

Ruminant Farm Systems is a modular, open-source, process-based platform for simulating physical and biological interactions at the farm level. As a whole-farm model, RuFaS predicts the essential outputs required for comprehensive assessment of environmental sustainability, including, milk, meat, and crop production, GHG emissions, ammonia (NH_3) emissions, water quality impacts, and soil carbon changes, in addition to many more detailed outputs depending on the use case. The core of the simulation model is 4 biophysical (animal, manure, soil and crop, and feed storage) modules that simulate the primary functions of a dairy farm on a daily timestep, including daily exchange of information between modules that reflects the integrated nature of a real dairy farm (Figure 2). Biophysical module execution is coordinated by a simulation engine that receives inputs from a flexible system for input data ingestion and that collects and records extensive, tailored outputs for further processing and analysis. When complete, the Economic Analysis Package will take advantage of these outputs to add economic metrics and comparisons to the sustainability outcomes predicted by the RuFaS model.

The "Animal Module" simulates the life cycle and productivity of dairy cattle at both the herd and individual animal levels and is described in detail by Hansen et al. (2021) and Li et al. (2023). It represents 5 life stages, from calf to mature cow, and accounts for reproduction, growth, lactation, and culling events. Herd initialization routines configure herd structure and pen assignments based on user-defined inputs, and herd management functions regulate animal grouping and size over time. Reproductive success and herd exits are determined probabilistically via event-based Monte Carlo simulation driven by user-specified inputs for onset of estrus, conception rate, pregnancy loss, death rate, and so on, as described in Li et al. (2023). Milk production is modeled using dynamic lactation curves (Gong et al., 2025), and diets can be defined by the user or formulated using a least-cost diet optimization algorithm

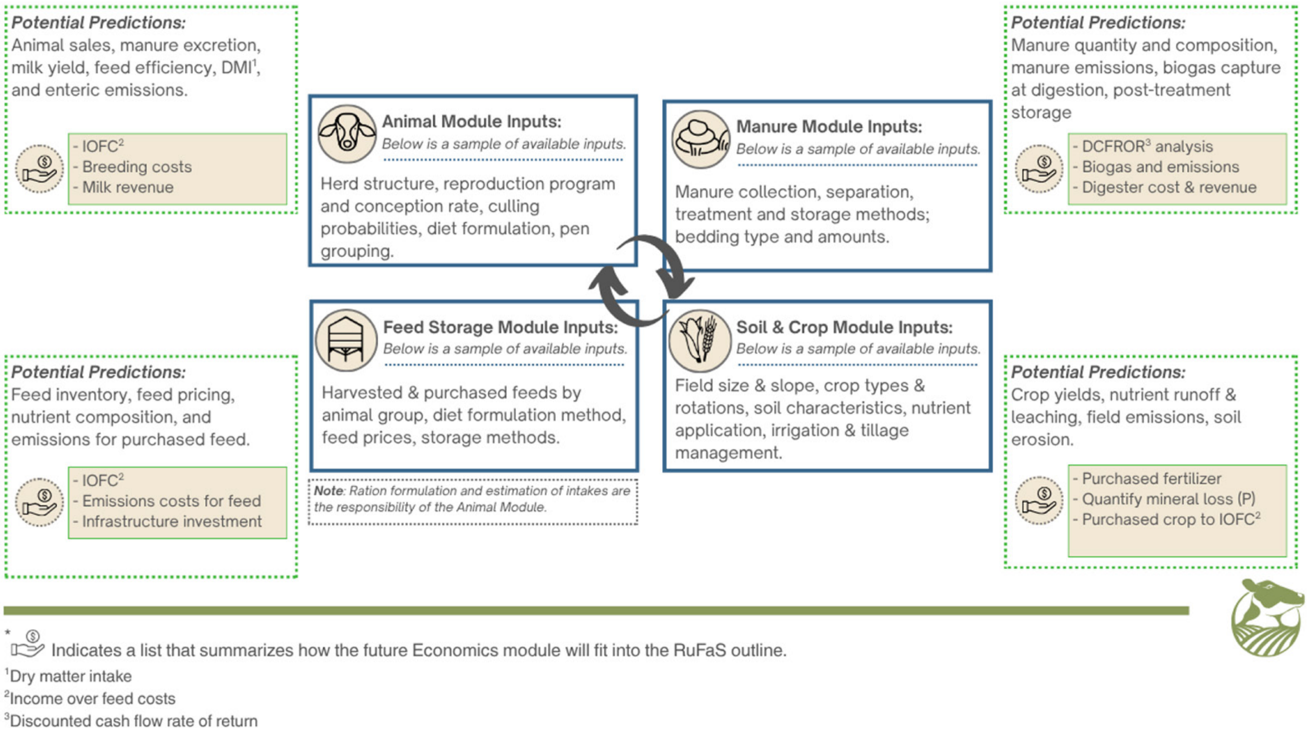

Figure 2. Select inputs, outputs, and processes simulated within the 4 core biophysical modules. A comprehensive description of the inputs and methods can be found in the RuFaS scientific documentation (RuFaS, 2025b).

informed by dairy cattle nutrient requirement models (NRC, 2001; NASEM, 2021) to ensure nutritional needs are met (Li et al., 2022). In addition to milk production and feed intake, the module predicts manure and urine output, enteric CH_4 emissions, and incorporates options for enteric CH_4 mitigation via 3-nitrooxypropanol or monensin feed additives. Perhaps the most innovative advancement of this module, however, is that it supports flexible herd structures with multiple pens, diverse breeding programs, and culling logic based on fertility and performance.

An example use case of the flexible herd structure is the comparison of different combinations of heifer and cow breeding programs on herd productivity and economic outcomes presented by Li et al. (2023). This work highlights the ability of RuFaS to compare complex and nuanced changes in animal management as illustrated in the 8 scenarios derived through combination of 3 heifer and 4 cow breeding strategies. The benefits of the extensive and diverse outputs produced by the model are also highlighted by the comparison of parity-specific reproduction and culling outcomes and pregnancy survival curves that provide additional context for interpretation of integrated metrics like annual milk production and net return.

Weigel et al. (2025) presented another application of the Animal Module in their assessment of the environmental impacts of genetic selection based on the dairy wellness profit index (**DWP$**). In that work, RuFaS model inputs were developed to represent theoretical herds that matched productivity and health attributes of high and low DWP$ cows from 11 different herds. By replicating the real-world productivity and health outcomes in RuFaS, Weigel et al. (2025) connected and quantified the expected change in environmental outcomes like the enteric CH_4 emission and N excretion intensity in response to changes in DWP$. This work provides an example of how RuFaS can be used to evaluate the effect of new technologies in cases where we still lack the scientific knowledge to specifically represent that technology in a process-based manner.

Other potential applications of the Animal Module include comparison of different nutritional strategies using the feeds available in the existing feed library, as illustrated by Hu et al. (2024), which compared outcomes from the automated ration formulation under 2 different nutrient requirement models, or by addition of new or novel feeds of interest as long as the required composition inputs can be supplied. There are also opportunities for extension of the first version of the Animal Module to open even further areas for investigation. Some of the future improvements planned for this module include representation of genetic inheritance and updates to the breeding and culling strategies that will expand the available herd management options.

The "Manure Module" represents manure as it moves through collection, storage, and treatment systems. Operating on a daily timestep, it simulates changes in manure mass, nutrient composition, and emissions across customizable manure management chains. The Manure Module includes routines for commonly used storage and treatment systems including solid-liquid separation, slurry storage, anaerobic lagoons, anaerobic digestion (**AD**), bedded packs, open lots, and composting. Each component employs equations specific to its process to estimate outcomes including nutrient losses, CH_4 production, and NH_3 volatilization. The module dynamically links to the Animal Module to receive manure excretion data and to the "Soil and Crop Module" for manure application scheduling. The flexible, modular design allows users to aggregate or split manure from different animal housing units in the Animal Module into specified chains that track manure from collection through long-term storage and application to the fields. Each manure management system is itself specified by the user and can be composed of a single or multiple treatment and storage methods sequentially linked.

The Manure Module thus supports holistic assessment of the impact of individual and combined elements of manure management, including trade-offs that might occur between CH_4 and NH_3 emission losses at different points along the management chain and nutrient composition at the time of field application. Furthermore, because the module receives manure directly from the Animal Module, it is well suited to assess interactions between diet, manure management, and environment as illustrated by Hu et al. (2025a). This use case compares production and emission outcomes of example farms in 3 different regions under 4 different manure management strategies as an evaluation of the model's ability to meet functional requirements for assessing interactions between diet and manure management. As expected, the results point to the potential of AD for reducing manure CH_4 emission when compared with slurry storage (0.341 vs. 0.495 kg CO_2-eq/kg of fat- and protein-corrected milk [**FPCM**]) but also highlight the trade-offs in N loss via NH_3 volatilization (8.98 vs. 7.38 g/kg of FPCM) in the 2 storage systems, which results from the increase in ammoniacal N concentration in AD digestate. The analysis by Hu et al. (2025a) also contextualizes the relative effects of manure management within the whole-farm footprint with the predicted differences in emissions associated with feed production for the simulated diets exceeding the predicted reductions in manure CH_4 achieved through AD. Other potential research applications of the Manure Module could compare different manure management scenarios for their effect on whole-farm nutrient efficiency, including variations in timing of manure application, extent of storage emptying, storage type, and use of storage covers. Similar to the Animal Module, the Manure Module has a low barrier for adaptation to test preliminary results from novel technologies like acidification or other manure treatments. Future work planned in this module will update the methods for AD to be responsive to varying management conditions, improve dynamic representation of emissions from solid storage systems, and update the underlying equations for NH_3 volatilization.

The "Soil and Crop Module" integrates soil biogeochemistry, crop growth, and field management to simulate nutrient dynamics and crop production. Drawing its process representations from 3 existing agronomic and soil biogeochemical models—SWAT (Nietsch et al., 2011), SurPhos (Vadas et al., 2007), and DayCent (Parton et al., 1987)—the Soil and Crop Module simulates soil nutrient cycling, water dynamics, and crop growth under varying management practices, soil conditions, and weather. The module coordinates daily operations such as manure and fertilizer application, tillage, planting, and harvesting across the user-defined number of fields. Soil routines model water balance, erosion, and transformations of nitrogen, phosphorus, and carbon pools, including soil carbon sequestration and GHG emissions. Crop growth is driven by solar radiation and captures biomass accumulation and nutrient uptake under varying conditions related to water, temperature, and nutrient availability. Harvested biomass is transferred to the "Feed Storage Module" for subsequent use in ration formulation, closing the nutrient loop between fields and animals. By representing interactions among soils, crops, and management, this module plays a pivotal role in assessing whole-farm nutrient efficiency and environmental sustainability.

Because the Soil and Crop Module replicates methods from existing models within RuFaS, its primary innovation and opportunity for application is its role in quantifying downstream effects of animal and manure management. Similar to the example of Veltman et al. (2017) discussed earlier, this module is essential for evaluating the relative effects and trade-offs of management strategies across the whole farm. Future work in this module will continue to improve the precision and accuracy of nitrous oxide emissions and soil carbon-sequestration estimates as scientific understanding of these processes and predictive capacity advance. Although current models largely focus on improving the accuracy of crop yield predictions in response to management and environmental conditions, there has been limited progress in linking these drivers to resulting feed composition and nutritional quality (Jones et al., 2017b). Adding this functionality will greatly improve the ability to predict the downstream impact of field management and environment on outcomes like animal feed efficiency and enteric CH_4 emission.

The Feed Storage Module functions as the central inventory system for harvested and purchased feeds, ensuring that feed availability and quality are accurately tracked throughout the simulation period. This module categorizes feeds into distinct storage classes (grain, hay, silage, and baleage), each subject to characteristic DM and nutrient losses during storage. Losses are calculated using fractional coefficients that reflect storage type and protection level, enabling dynamic adjustments to feed quality over time. Harvested biomass from the Soil and Crop Module and purchased feeds enter the storage system, where nutrient composition is updated to reflect storage effects before being allocated for ration formulation in the Animal Module. By modeling feed losses and inventory management, the Feed Storage Module provides a realistic basis for evaluating ration strategies, feed costs, and their effect on farm productivity and sustainability. There are many opportunities to expand the functionality of this module, including improved process-based representation of spoilage and the effects of inoculants; however, in the context of whole-farm sustainability, the primary benefit of this module is in its ability to complete the nutrient cycle on the farm from crop production to animal feeding and to manage and report daily feed use and inventory.

The proposed "Economics Analysis Package" is under development and will integrate cost and revenue streams associated with milk production, feed procurement, manure handling, and environmental compliance. It aims to simulate profitability under different management scenarios and policy incentives, supporting assessments of economic trade-offs alongside environmental outcomes. When completed, the built-in Economic Analysis Package will allow users to conduct these economic assessments using outputs generated by the RuFaS model directly, rather than requiring an additional post hoc analysis. Although the package will provide sets of default price and cost data, a key feature will be the user's ability to provide their own economic data inputs, so the results represent the current state and specific conditions of inquiry.

The RuFaS model outputs, with the completion of the 4 core process-based biophysical modules described herein as a modular, farm systems modeling framework, now includes estimates of production responses, nutrient cycling, and emissions across the whole farm. These outputs can help scientists explore cross-system interactions of their research, anticipate unintended trade-offs in sustainability metrics, and identify knowledge gaps requiring further empirical study (Figure 1). As early applications illustrate (Table 1), RuFaS transforms the farm into a computational laboratory where scenarios, ranging from genetics and nutrition to manure management and cropping practices, can be digitally and transparently evaluated.

Comparison of RuFaS to existing whole-farm models, such as IFSM (Rotz et al., 2018) and DairyMod (Johnson, et al., 2008) illustrates how RuFaS has drawn from the strengths and improved on shortcomings in other models. First, RuFaS is designed to support modular, multiscale modeling, allowing users to simulate processes at the field, herd, and farm levels independently or in combination. This flexibility is conceptually similar to modularity seen in IFSM and COMET-Farm in that it enables researchers to tailor the model application to specific research questions or data availability, but the combination of object-oriented programming and process-based modeling in RuFaS expands the biological scales that are represented (i.e., from herd to pen or animal) and dynamically shares information between modules to increase understanding of downstream effects. Second, RuFaS enables users to run multiple model configurations or parameter sets in parallel, which enhances the robustness of predictions and supports uncertainty analysis, capabilities that are increasingly important in climate and sustainability research and not available as built-in functionalities of other whole-farm models. Like other whole-farm models, this feature also allows users to define and compare alternative management or policy scenarios within a consistent modeling framework, supporting decision making at multiple levels.

Third, RuFaS's modular architecture and adherence to clean code principles enable rapid prototyping of new modules and functions, unlike legacy systems that are difficult to expand. Furthermore, with modern version-control methods, researchers can develop and test new components like alternative feeding strategies, manure management technologies, or climate scenarios without disrupting the core model. Methods for using and contributing to RuFaS are clearly described on the repository in the README files and supplementary documentation on GitHub pages (RuFaS, 2025a). Fourth, the model includes a built-in data harmonization layer, which standardizes inputs and outputs across modules. This reduces the burden of data preprocessing and lays the groundwork for future interoperability with external datasets and tools for farm data management. Finally, RuFaS includes a transparent and extensible output manager for model diagnostics and visualization that allows users to trace detailed intermediate outcomes that drive model behavior, identify anomalies, and communicate results effectively. These features collectively distinguish RuFaS from other whole-farm models and position it as a flexible, extensible, and scientifically rigorous platform for whole-farm systems modeling.

Commitment to open science and open-source software development drives RuFaS program investment in documentation, selection of the GNU General Public License v3.0 (**GPLv3**), and the mechanisms of distribution. The United Nations Educational, Scientific, and Cultural Organization (**UNESCO**) defines open science as a means "to make multilingual scientific knowledge openly available, accessible, and reusable for everyone, to increase scientific collaborations and sharing of information for the benefits of science and society, and to open the processes of scientific knowledge creation, evaluation, and communication . . . beyond the traditional scientific community" (UNESCO, 2021, p. 7). Similarly, open source is a software development paradigm grounded in the principles of freedom, transparency, and collective advancement. The Open Source Initiative (2006), defines open-source software as freely accessible, modifiable, and redistributable by anyone. The Free Software Foundation (2024) further emphasizes that users should have the freedom to run, study, change, and share software for any purpose.

In the context of agricultural and environmental modeling, combining open science and open-source software development enables researchers to examine and validate model assumptions, adapt tools to local conditions, and contribute improvements that benefit the broader community. It also facilitates integration across disciplines and institutions, increasing collaboration and allowing scientists to build on each other's work. As scientific challenges become more complex and urgent, particularly those related to food systems and sustainability, open-source models offer a pathway to accelerate discovery and democratize innovation.

The RuFaS model adheres to open-source principles through its transparent, community-oriented development process. Under the terms of the GPLv3 license, any modified versions or derivative works must also be distributed under the same license, preserving the freedoms to use, study, modify, and share the RuFaS codebase. In addition, RuFaS includes the GNU Lesser General Public License v3.0 for the use and distribution of its libraries. This allows RuFaS libraries to be dynamically linked with proprietary software without requiring the entire combined work to be open sourced, which is an important consideration for integration into larger systems or commercial applications.

The RuFaS codebase is hosted in a public repository on GitHub (https://github.com/RuminantFarmSystems/RuFaS), where it is actively maintained and openly documented. GitHub is a global communication and version-control platform that enables community-driven development, rigorous code review, and rapid integration of new scientific insights. The mechanisms for coding and noncoding contributions to RuFaS are clearly documented on CONTRIBUTING.md file in the RuFaS GitHub repository root directory (https://github.com/RuminantFarmSystems/RuFaS/blob/dev/CONTRIBUTING.md). This file also includes descriptions of the process for code review and coding conventions, as well as expectations and responsibilities assumed by contributors as their level of involvement increases from RuFaS users, contributors, and sponsors to maintainers and program management leaders. In particular, the RuFaS Program Management Leadership is responsible for providing strategic direction and governance, approving all codebase releases, managing contributor privileges, resolving disputes, and ensuring that RuFaS development aligns with community needs and open-source principles. The RuFaS approach to codebase development, maintenance, and distribution was developed to foster transparency, collaboration, and innovation. Although the repository and its GPLv3 license meet the formal criteria for open-source classification, true accessibility requires that users can understand how to use, modify, and interpret the model. To support this, significant effort was invested in the clarity and availability of the codebase and model documentation. The scientific foundations of the biophysical modules are described in the RuFaS project scientific documentation (RuFaS, 2025b) and are freely available on the repository. This level of transparency allows users to trace model logic, validate outputs, and contribute improvements through version-controlled collaboration.

The RuFaS codebase is written in Python and follows the SOLID (Single responsibility, Open-closed, Liskov substitution, Interface segregation, and Dependency inversion) principles of object-oriented design (see Martin, 2003 and Martin, 2017). This structured approach enhances readability for developers and makes the underlying logic more approachable for subject matter experts without extensive programming experience, while also improving the code's adaptability and ease of maintenance over time. By adhering to this software design philosophy, RuFaS can support active engagement by the scientific community, accelerate model improvement, innovation and discovery and create educational opportunities for students and practitioners.

In summary, RuFaS was designed as a modeling platform for transdisciplinary scientific collaboration. Its open-source foundation and modular design invite researchers from diverse fields to collaboratively create knowledge, test hypotheses, and inform real-world decisions. By integrating biophysical processes with management practices, RuFaS enables holistic assessments of sustainability outcomes across scales and systems. Its accessibility and adaptability make it suitable for a wide range of applications, from academic research and extension to policy analysis and education. Scientists can use RuFaS to explore complex interactions within ruminant farming systems, evaluate the effects of alternative practices, and develop strategies with stakeholders to meet sustainability goals and stewardship commitments across the dairy supply chain. Its transparent development process encourages contributions from across the scientific community, intended to foster a shared sense of ownership and purpose. Through developing new modules, refining existing ones, and applying the model in novel contexts, scientists, educators, and practitioners can contribute to the RuFaS modeling platform as it evolves with the needs of the dairy sector.

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Nonstandard abbreviations used: AD = anaerobic digestion; DCFROR = discounted cash flow rate of return; DWP$ = dairy wellness profit index; IFSM = Integrated Farm Systems Model; IOFC = income over feed costs; FARM = Farmers Assuring Responsible Management; FARM-ES = FARM environmental stewardship; FPCM = fat- and protein-corrected milk; GPLv3 = GNU General Public License v3.0; RuFaS = Ruminant Farm Systems; UNESCO = United Nations Educational, Scientific, and Cultural Organization.

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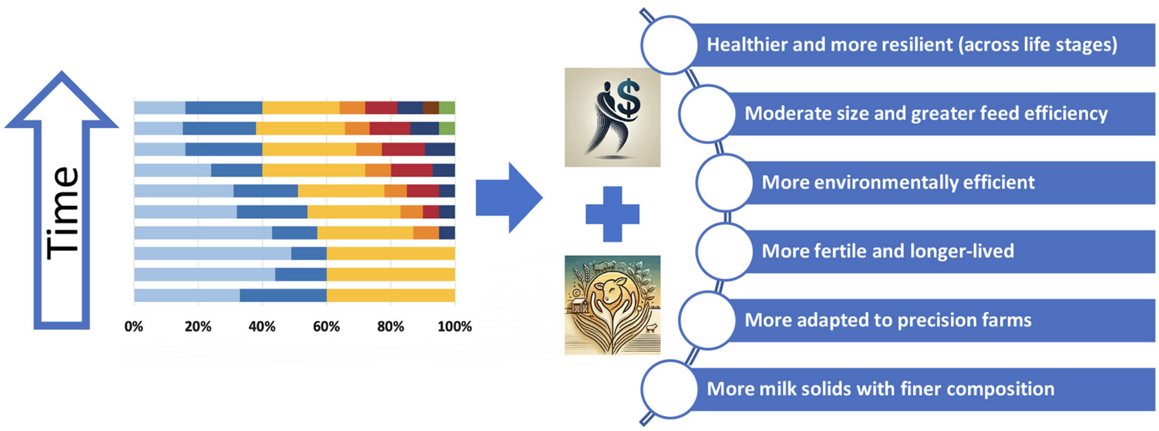
Invited Review
Genetics

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

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

Graphical Abstract

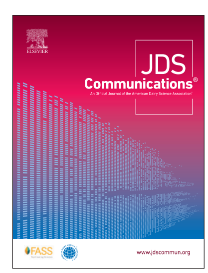


Summary

Future dairy cows will be healthier, longer-lived, and more fertile, with improved resilience and feed efficiency, and lower methane emissions. Advances in genomics, phenomics, and precision technologies will drive balanced genetic improvement in productivity, adaptability, welfare, and environmental sustainability. Selection indexes are being continually refined to enable coordinated genetic progress across these diverse breeding goals. Modern breeding programs will integrate genomic selection, automated phenotyping, and responsible management of genetic diversity to develop efficient and sustainable dairy populations.

Highlights

- Genomics and phenomics will define the dairy cow of the future.
- Future cows will be healthier, more resilient, and longer-lived.
- Precision technology enables selection for welfare and efficiency.
- Safeguarding genetic diversity is the key to sustainability.



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Abstract: The dairy industry has experienced unprecedented genetic progress, more than doubling milk yield over recent decades, but this has often resulted in reduced fertility, longevity, and robustness. This review addresses the question "Who will be the dairy cows of the future?" by highlighting the integration of genomics, phenomics, and advanced breeding strategies. From our perspective, future cows are expected to be healthier, more resilient, and longer-lived, with improved fertility, feed efficiency, and reduced methane emissions. Precision technologies, wearable sensors, and automated systems are providing novel phenotypes and driving selection for adaptability, welfare, and efficiency. Genomic selection, reproductive and other biological technologies, and beef-on-dairy crossbreeding are reshaping dairy breeding programs, while collaborations are critical for advancing multiple-trait evaluations and safeguarding genetic diversity. Despite Holstein breed dominance, maintaining across- and within-breed variation is essential for long-term sustainability. Ultimately, as a consequence of the wide adoption of precision technologies, more complex breeding goals, and effective breeding strategies, the dairy cow of the future will balance productive efficiency with resilience, welfare, and environmental efficiency, ensuring global sustainability of dairy production.

The global dairy cattle industry has changed dramatically over the past century, with milk production per lactation more than doubling in recent decades (Brito et al., 2021), largely due to genetic improvement (Figure 1). However, the large increase in milk productivity per lactation has been accompanied by reduced fertility and longevity, as well as higher incidence of infectious and metabolic diseases (Lucy, 2001; Miglior et al., 2017). These negative consequences were mainly the result of an intensive and long-term focus on selection for milk production traits alone (Miglior et al., 2017). Fortunately, this trend began to shift toward the end of the last century, driven by advances in computational capacity and the implementation of dairy cattle breeding programs that directly targeted fertility, health, longevity, and other functional traits (Cole and VanRaden, 2018; Brito et al., 2021). Multiple-trait selection has become possible through major advancements in phenotyping tools and data collection systems, which, when combined with genomic selection, reproductive technologies, and improved management practices, have accelerated the rates of genetic and phenotypic change in worldwide dairy cattle populations. Dairy farms are also getting larger and labor shortages are becoming a challenge in many countries (Charlton and Kostandini, 2021). From another angle, society expects an increased and more affordable supply of milk and other dairy products made with milk from healthy cows requiring less veterinary medical treatments and being raised under exemplary welfare conditions (Barkema et al., 2015). This should be accomplished while minimizing the environmental impacts of the dairy industry. Precision technologies and wearables sensors are being increasingly used in dairy farms to optimize management, mitigate labor shortages, improve animal and farmer welfare, and generate large-scale datasets for developing novel traits and breeding goals (Brito et al., 2020a, 2025). Under these circumstances, dairy producers operate with narrow profit margins and are being required to innovate to remain competitive in the food market. In this context, the main objective of this article is to provide a perspective on the future of dairy cattle breeding by addressing the question "Who will be the dairy cows of the future?" More specifically, we discuss the key trait groups, emerging technologies, and stakeholders' decisions or actions that are shaping, or are likely to shape, the dairy cow of the future, with particular emphasis on breeding programs in developed countries.

Before envisioning the cow of the future, it is important to revisit past events. Following cattle domestication over 10,000 yr ago (Pitt et al., 2019), farmers began selecting breeding animals based on a limited number of traits of interest. This early domestication and selection process led to the formation of specialized breeds for distinct purposes such as meat, milk, or draft. Initially, selection relied exclusively on observable phenotypes, with little or no systematic record keeping. The primary traits targeted under artificial selection included temperament, milk yield, and physical attributes such as coat color, presence of horns, and body conformation. Despite the limited scope of phenotypic recording, substantial genetic progress was achieved for traits with moderate to high heritability such as temperament (Chang et al., 2020; Pacheco et al., 2025).

Systematic phenotypic data collection in dairy cattle populations began in the late 19th and early 20th centuries, particularly in Europe and North America, driven by the need to increase milk production and overall herd performance. Dairy Herd Information Associations with organized milk recording systems were established in the early 1900s (Voelker, 1981). For many decades, phenotypic recording and pedigree-based selection relied primarily on low-frequency measurements (e.g., monthly) of milk yield and milk composition, followed later by body conformation traits (Miglior et al., 2017). From the 1980s onward, data collection schemes expanded to include a broader range of traits related to

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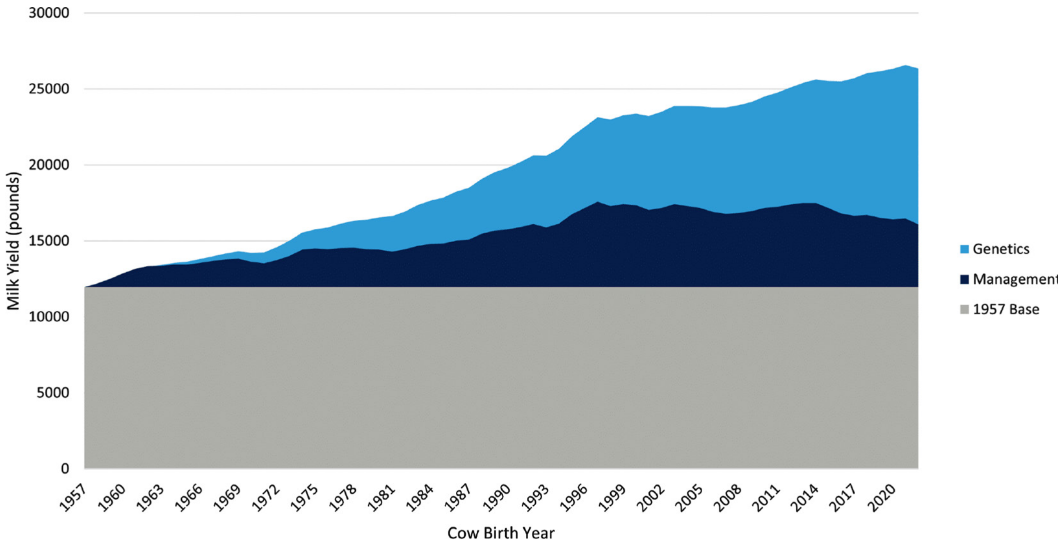

Figure 1. Changes in US Holstein milk production from 1957 to 2022, indicating the proportional contributions of genetics and management practices. Source: Council on Dairy Cattle Breeding (CDCB, 2025b).

performance, reproduction and fertility, cow longevity, health and welfare, and environmental efficiency (e.g., feed efficiency, methane emissions; Cole and VanRaden, 2018; Brito et al., 2021, 2025).

In the late 1990s, there was a need and an opportunity to develop more complex selection objectives that emphasized economic and societal importance of the individual traits simultaneously. Since then, multiple-trait selection indexes have been continually updated to reflect emerging breeding goals (Cole and VanRaden, 2018), which are contributing to shape the dairy cow of the future. Nevertheless, many traits of growing importance (e.g., health, welfare, and fertility-related traits) remain difficult to measure and generally have low heritabilities (Maskal et al., 2024). Their quantification generally requires continuous and large-scale recording, which remains a challenge. The implementation of genomic selection around 15 to 20 yr ago revolutionized dairy cattle breeding by facilitating the genetic evaluation of traits that are lowly heritable, expensive or difficult to measure, sex-limited, or expressed late in life (Brito et al., 2021; Guinan et al., 2023). Genomic selection has increased annual genetic progress by improving the accuracy of breeding values of younger animals, enhancing selection intensity, and substantially reducing the generation intervals in dairy cattle breeding programs (Guinan et al., 2023). Coupled with large-scale phenotyping, genotyping has now become routine in most major dairy populations, where reference populations comprising hundreds of thousands to millions of animals provide the foundation for highly accurate genomic predictions for many key traits. In the United States alone, more than 10 million dairy animals have been genotyped, of which ~93% are female (CDCB, 2025a). Genomic datasets have been applied to a wide range of purposes, including genomic selection, parentage verification and correction, estimation of breed composition, culling decisions, optimization of mating schemes (e.g., identifying cows to be inseminated with beef semen in beef-on-dairy crossbreeding), and mating allocations to minimize inbreeding, among other applications. Furthermore, the identification and elimination of harmful recessive alleles has become a standard practice, with tools now routinely available to reduce the incidence of genetic defects and improve population health (Cole et al., 2025).

In addition to productive and reproductive efficiency, the dairy cow of the future must also exhibit superior health, welfare, and resilience to thrive within modern production systems and to meet society's expectations for responsible animal care. In this context, health and welfare traits are gaining prominence in breeding programs (Cole and VanRaden, 2018; Brito et al., 2020a), not only due to their direct economic impact but also in response to increasing public concern for animal well-being. Furthermore, as climate change continues to threaten livestock production, the dairy cow of the future will need to be more resilient for sustaining high performance across diverse and unpredictable environments and management conditions (Misztal et al., 2025). Resilience is defined as the capacity of animals to be minimally affected by disturbances or to rapidly recover from them (Colditz and Hine, 2016), which can be operationalized as the ability to withstand environmental stress, disease, or management challenges while maintaining productivity and recovering quickly from temporary reductions in performance. In recent years, various indicators of overall resilience have been proposed based on variability in longitudinally recorded variables such as milk yield (Poppe et al., 2020; Chen et al., 2023), activity level (Poppe et al., 2022), and calf milk consumption (Graham et al., 2024). Variance-based resilience indicators are based on the principle that more resilient animals exhibit less variation in performance measures over time. Conversely, high values of these indicators reflect lower resilience, as such animals display greater fluctuations in response to environmental challenges. Most resilience indicators proposed so far are heritable (Maskal et al., 2024; Brito et al., 2025) and can, therefore, be improved through genetic selection. A recent meta-analysis by Maskal et al. (2024) reported substantial variability in the genetic relationships between resilience and productivity traits, but provided strong evidence that simultaneous genetic improvement in both trait groups is achievable when they are jointly incorporated into selection indexes.

Intensive selection for higher milk yield has likely resulted in greater heat stress sensitivity (Boonkum et al., 2024; Misztal et al., 2025), indicating the need to breed for improved heat tolerance. The most common methods for estimating breeding values for heat tolerance largely focus on variability in production performance under thermal stress conditions, and the incorporation of genomic information has significantly improved prediction accuracy (Nguyen et al., 2016; Misztal et al., 2025). However, selecting solely for animals that maintain production during heat stress may increase mortality risk and welfare issues, highlighting the complexity of balancing breeding objectives. Therefore, there is a need for developing novel traits related to physiological, behavioral, and anatomical characteristics that may capture variability in heat tolerance more independently of milk production, thereby enabling more holistic and effective breeding for heat tolerance (Brito et al., 2025; Misztal et al., 2025). Another technology that may become highly relevant in this regard is gene editing (Van Eenennaam, 2019). Key mutations associated with heat tolerance, such as the prolactin receptor (*PRLR*) gene ("SLICK hair"), can be efficiently edited to introduce favorable alleles from more heat-tolerant cattle breeds such as Senepol into high-producing dairy breeds such as Holstein (Sonstegard et al., 2024).

The cow of the future will be healthier than today's cows. Although health traits in dairy cattle typically exhibit low to moderate heritability, they generally show substantial additive genetic variation, indicating that meaningful genetic progress can be achieved through direct selection (Zavadilová et al., 2021; Brito et al., 2025). This progress is further accelerated when genomic information is incorporated into the prediction of breeding values. Mastitis remains one of the most prevalent and costly infectious diseases in dairy cattle, and genetic selection for reduced clinical mastitis incidence, as well as for auxiliary traits such as SCS, has proven effective (Martin et al., 2018). Beyond mastitis, numerous health traits have either already been incorporated into national selection indexes or are in advanced stages of genetic evaluation and implementation. These include metabolic and digestive disorders such as ketosis and displaced abomasum, as well as lameness, hoof health, retained placenta, metritis, and respiratory diseases (Jamrozik et al., 2016a,b). There will also be a greater focus on traits related to calf health and efficiency. Continued expansion of routine phenotyping, combined with genomic prediction and high-throughput phenotyping using sensors and other technologies, will enhance the accuracy of selection for these traits and contribute to a more resilient and robust dairy cow.

Accurately measuring health and welfare traits remains challenging because many health conditions occur at relatively low frequency and their assessment or diagnosis is often subjective. Traditional recording approaches, based on producer reports or veterinary diagnoses, are often prone to incompleteness or inconsistency. To overcome these limitations, the development of objective and automated measurement systems is essential. Sensor technologies provide promising tools for continuous monitoring of health and welfare (Brito et al., 2020a, 2025). For example, activity monitors can detect behavioral changes indicative of illness or distress, whereas automated systems for recording rumination, feeding behavior, and lying patterns provide valuable insights into metabolic status and overall well-being. Moreover, the integration of multiple sensor data streams through machine learning and predictive modeling has the potential to enhance the accuracy and reliability of health and welfare assessments (Marzougui et al., 2025).

The rapid adoption of automated milking systems (**AMS**; also termed milking robots) and other precision technologies and wearable sensors in dairy farming may reshape the ideal dairy cows. The dairy cow of the future must not only possess structural soundness for longevity, efficiency, and welfare but also physical and behavioral characteristics that facilitate efficient interaction with automated systems. This represents a major shift from traditional breeding objectives, which were historically oriented toward human-operated farming. For instance, AMS rely on predictable udder characteristics for accurate teat detection and attachment as well as cow behavior. The ideal udder is characterized by appropriate height and depth, strong attachments, and optimal teat placement, length, and width. The AMS provide useful data for deriving relevant udder conformation traits based on XYZ cartesian coordinates, which are moderately to highly heritable (Medeiros et al., 2024). Milking speed is another heritable trait of high economic relevance in AMS herds. Faster-milking cows improve AMS throughput, enabling more cows to be milked per unit per day. Milking speed is a moderately heritable trait and is favorably correlated with milk yield (Pedrosa et al., 2023). Beyond milking speed, cow behavior in AMS is also highly relevant for system efficiency and animal management, and several cow behavioral traits have been shown to be heritable (Bérat et al., 2025). These include the time interval between successive milkings, the number of attempted visits to the AMS, the number of successful entries, the proportion of successful milkings, and the cow preference consistency score, all of which reflect the adaptability of cows to AMS (Bérat et al., 2025; Brito et al., 2025).

Docility, easy social interaction, and behavioral plasticity represent critical traits that influence both animal welfare and operational efficiency in modern dairy systems (Pacheco et al., 2025). Temperament, often called docility, represents one of the most important behavioral traits in dairy cattle due to its direct relationship with animal welfare, handler safety, and production efficiency. Docile cattle are easier and safer to handle, require less labor for routine management procedures, and show better adaptation to modern production systems. The economic impact of temperament extends beyond labor efficiency to include effects on milk production, reproductive performance, and longevity (Pacheco et al., 2025). Temperament traits in dairy cattle show moderate to high heritability (Chang et al., 2020; Pinto et al., 2025), depending on the specific trait definition and measurement method. These heritability values indicate that genetic improvement through selection is highly possible and can achieve substantial progress within relatively few generations.

Feed typically accounts for 50% to 70% of total production costs in dairy production systems, making feed efficiency a primary driver of economic success. Therefore, dairy cattle producers are increasingly prioritizing feed efficiency in their breeding objectives and various countries have already included it in their selection indexes (Manzanilla-Pech et al., 2022). Feed efficiency directly influences farm profitability, environmental sustainability, and the efficient use of resources. Several traits have been proposed or used for genetically improving feed efficiency in dairy cattle, including feed conversion ratio, residual feed intake (**RFI**), DMI, and efficiency ratios that consider both maintenance requirements and milk production (Tempelman and Lu, 2020). Residual feed intake is the most common feed efficiency trait in dairy cattle research and breeding programs because of its independence from production level and body size (Roche et al., 2018; Stephansen et al., 2024). This measure is calculated as the difference between actual feed intake and predicted feed intake based on BW and milk production (Tempelman and Lu, 2020; Stephansen et al., 2024). Animals with negative RFI values are more efficient because they eat less feed than predicted for their level of production. In addition to within-animal efficiency traits, broader indicators of overall cow efficiency are increasingly relevant for both management and breeding purposes, including milk solids yield relative to BW or ECM per unit of metabolic weight. These measures, although less precise in isolating biological efficiency, are easier to record on a large scale and often align closely with farm profitability.

Feed efficiency traits are moderately heritable, with estimates typically ranging from 0.1 to 0.4 depending on the specific trait definition and population studied (Brito et al., 2020b). The genetic control of feed efficiency is complex, involving multiple biological pathways related to digestion, metabolism, and energy use (Brito et al., 2020b; Jiang et al., 2024). One of the main challenges in improving feed efficiency through genetic selection is the difficulty and high cost of collecting accurate individual feed intake data on many animals. Traditional measurement approaches require specialized equipment and intensive management, which restricts the number of animals that can be evaluated. Recent technological advances are helping to overcome these barriers through the development of automated feed intake monitoring systems that employ electronic identification, load cells, and computer vision to continuously record individual animal feed consumption (Ojo et al., 2024). A promising feed intake recording system is the Cattle Feed Intake and Tracking (CFIT) system, which is an automated technology that uses 3-dimensional cameras and computer vision to continuously measure individual feed intake and feeding behavior of dairy cows under commercial conditions (Giagnoni et al., 2024). It provides accurate, noninvasive phenotyping at large scale, enabling genetic selection for feed efficiency and related traits. The integration of sensor technologies with feed intake measurements is creating new opportunities for genomic evaluations. Wearable devices can continuously monitor traits such as rumination, activity, and other behavioral indicators that may be associated with feed efficiency (Lopes et al., 2024). Combining these diverse data sources through machine learning approaches may improve the accuracy of efficiency predictions while reducing the cost of trait measurement (Shadpour et al., 2022).

Over the past years, there has been an increased global effort to reduce GHG emissions, particularly methane, including from livestock production. Dairy cattle alone account for ~4% of anthropogenic GHG emissions worldwide (Singaravadivelan et al., 2023). In addition to being more feed efficient, the dairy cow of the future is expected to produce substantially less methane. Methane is a natural byproduct of rumen fermentation, where specific microorganisms convert hydrogen and carbon dioxide into methane as part of the normal digestive process. This process represents an energy loss of ~6% to 12% of total energy intake, making methane reduction beneficial from both environmental and efficiency perspectives (Roche et al., 2018). There is substantial additive genetic variability in methane emission traits, with heritability estimates typically ranging from 0.15 to 0.35, depending on the trait definition and measurement method (Richardson et al., 2021; Kamalanathan et al., 2023). Various methane emission traits have been proposed, including total methane production, methane yield per unit of feed intake, and methane intensity per unit of milk production (Kamalanathan et al., 2023). The positive genetic relationship between methane production and milk yield (Pszczola et al., 2019; Rojas de Oliveira et al., 2024) suggests that selection for milk yield and fat content may inadvertently increase methane emissions, highlighting the importance of balanced breeding goals.

A major challenge for the genetic improvement of methane traits has been the difficulty and costs of accurately measuring individual emissions. Respiration chambers are accurate but costly and labor-intensive, which restricts their application in large-scale breeding programs. Recent technological advances have enabled the development of more scalable measurement approaches such as GreenFeed machines, laser methane detectors, and infrared sensors integrated into feeding systems or milking parlors (Ghassemi Nejad et al., 2024). Mid-infrared analysis of milk has also proven useful for predicting methane emissions with moderate accuracy and has been implemented in the national genetic evaluation schemes from Canada (Rojas de Oliveira et al., 2024). In addition, rumen microbial indicators, milk fatty acid profiles, and other biomarkers are under investigation as potential proxies for methane production. The genetic relationships between methane emissions and other economically important traits also indicate that genomic selection for reduced methane emissions without compromising performance is possible when appropriate trait definitions and selection strategies are applied (Kamalanathan et al., 2023; Rojas de Oliveira et al., 2024).

While incorporating an increasing number of traits in selection indexes enables more comprehensive and sustainable breeding objectives, it also dilutes the rate of genetic progress achieved for individual traits. According to selection index theory, when multiple traits are included with meaningful (bioeconomic) weights, the overall genetic gain is distributed across them in proportion to their relative importance and genetic correlations. Therefore, the inclusion of additional traits such as welfare, resilience, or environmental efficiency may reduce the short-term response in production traits but contributes to greater overall herd sustainability. Future breeding goals should thus be designed to achieve an optimal balance between productivity, animal well-being, and environmental impact rather than maximizing progress in any single trait.

International collaborations are essential for advancing genomic selection in dairy cattle, as they enable the pooling of large-scale data across countries, which can increase accuracy of breeding values and facilitate the development of robust models that are applicable to diverse populations (van Staaveren et al., 2024). Organizations such as the International Committee for Animal Recording (ICAR; https://www.icar.org) play a critical role in standardizing methodologies, fostering data exchange, and ensuring international comparability of evaluations, thereby strengthening global genetic improvement programs.

More recently, there has been an increasing control of data from sensors and other precision technologies by private companies or manufacturers, which limits farmer ownership and accessibility to raw phenotypic data. This shift has important implications for genetic improvement programs, as it may restrict the availability of large-scale, high-quality phenotypes that are essential for developing accurate genetic evaluations (Brito et al., 2025). Another highly relevant aspect of dairy cattle breeding, beyond breeding goals and

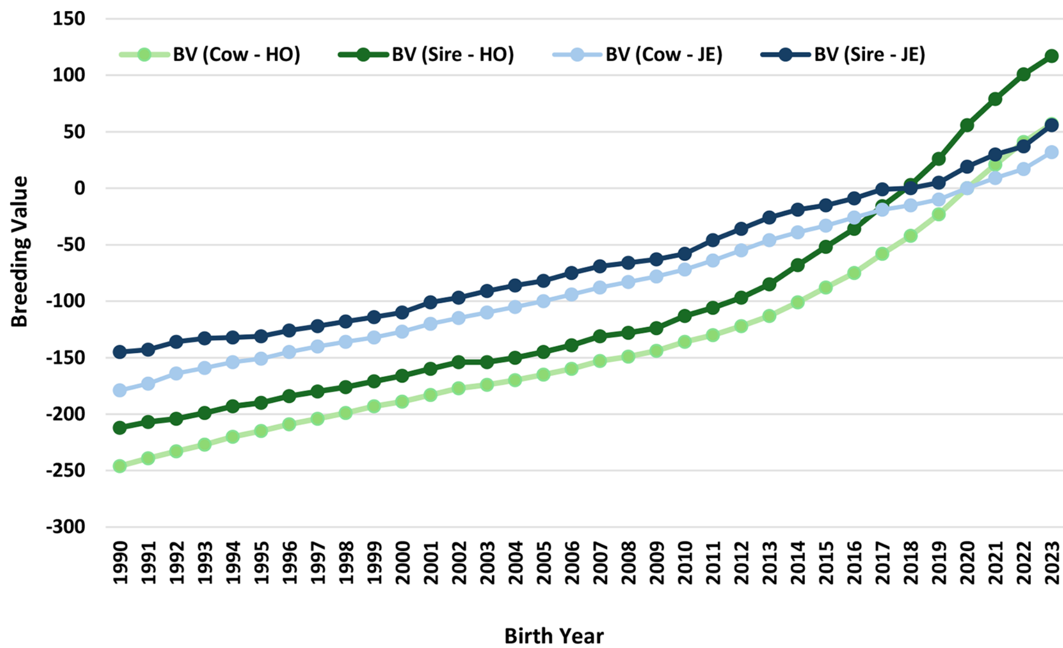

Figure 2. Genetic trends for milk fat content in US Holstein (HO) and Jersey (JE) cattle separated by cow and sire breeding values (BV). Source: Council on Dairy Cattle Breeding (CDCB, 2025b).

phenotyping schemes, is the maintenance of genetic diversity both across and within breeds. Since domestication, hundreds of cattle breeds have been developed, but only a few dominate the dairy cattle sector, particularly the Holstein breed. In many countries, Holsteins represent ~90% of the dairy cattle population and benefit from the largest dairy reference populations for genomic selection. For example, the CDCB genomic database includes 12 breeds, but 89% of the genotypes are from Holsteins and 10% from Jerseys (CDCB, 2025; https://uscdcb.com/database-stats/). Most novel traits are usually implemented first, and sometimes exclusively, in Holstein breeding programs, which further reinforces the breed's competitiveness. The large proportion of genotyped Holstein animals enables greater selection intensity; larger reference populations result in more accurate breeding values and, consequently, faster rates of genetic progress. For instance, Jerseys have traditionally been recognized for their high milk fat content. However, in recent years, the average breeding values of Holstein bulls have surpassed those of Jersey bulls, and Holstein cows now present values similar to Jersey bulls and higher than Jersey cows (Figure 2). Although many non-Holstein breeds possess unique advantages, the disproportionate availability of reference populations for novel traits, combined with the widespread adoption of reproductive tools and genomic technologies, may further increase Holstein's dominance. Without deliberate efforts at national and global levels to develop multicountry reference populations for smaller dairy breeds, and without strategies that ensure the long-term sustainability of dairy cattle breeds, across-breed genetic diversity may continue to erode.

In addition to maintaining across-breed genetic diversity, within-breed genetic variability is of utmost importance. The annual rates of inbreeding in dairy cattle populations continue to increase (Brito et al., 2021; CDCB, 2025a), especially as generation intervals went down with the implementation of genomic selection (Guinan et al., 2023). Inbreeding is well known to have an unfavorable effect on livestock traits. For instance, based on a meta-analysis of 30 yr of research, Doekes et al. (2021) found that a 1% increase in pedigree inbreeding is associated with a median decrease in phenotypic value of 0.13% of a trait's mean and 0.59% of a trait's standard deviation. Inbreeding can also result in greater expression of alleles with unfavorable or deleterious effects in homozygous state. At the same time, genomic information can be used for more accurately assessing the relationship among animals, and therefore avoid mating of highly related animals, as well as more accurate inbreeding assessment based on metrics that separate ancient from more recent inbreeding (Meuwissen et al., 2020; Mulim et al., 2022). As more genomic data become available, more deleterious alleles can be detected in the populations, and used when doing selection and matings, as reviewed by Cole et al. (2025). A greater effort by all dairy sector stakeholders should be made to maintain within-breed genetic diversity and minimize the rates of inbreeding in dairy cattle populations. Meuwissen et al. (2020) describes various strategies for the management of genetic diversity in the genomics era. In brief, genomics data allow for calculation of many alternative measures of inbreeding and genomic relationships that can be used to manage genetic diversity in genomic optimal contribution selection schemes. Tools such as gene editing may also be used in the future for precisely removing deleterious or unfavorable alleles or adding genetic variability to targeted regions of the genome.

The dairy sector is experiencing a growing adoption of beef-on-dairy crossbreeding schemes (Berry, 2021), in which dairy cows (typically those with lower genetic merit) are inseminated with semen from beef bulls to produce offspring destined for the beef market. In contrast, dairy cows of higher genetic merit are inseminated with female sex-sorted semen to generate replacement heifers. Based on current market trends, it is expected that the vast majority (e.g., >90%) of dairy cows in the future will be inseminated with sex-sorted semen. In addition to such terminal crossbreeding strategies, dairy–dairy crossbreeding has also been widely adopted in some countries. For example, in New Zealand, the Kiwi Cross, resulting from crosses between Holstein and Jersey cattle, is a prominent system. Similarly, composite breeds and other crossbreeding schemes are popular in some countries. For instance, Girolando, a cross between Holstein and Gyr (*Bos taurus indicus*), is popular in Brazil due to its enhanced productivity and improved adaptation to hot and pasture-based production systems. From a crossbreeding perspective, selection pressure within dairy populations may increasingly favor cows that are more fertile, easy-calving, and capable of producing calves with acceptable growth and carcass traits when mated with beef sires, without compromising their own lifetime productivity and welfare.

There may also be some restructuring of the dairy sector in the coming decades. Various artificial insemination companies are developing contracts with dairy farmers for the collection of specific phenotypes of novel traits for providing customized genomic evaluations and also agreements for semen purchases and purchase of male calves to become breeding bulls. If continued, this may lead to a verticalization of the dairy breeding sector and the formation of subpopulations around artificial insemination companies. This could result in challenges for national and international genetic evaluations such as reduced connectedness among herds. Additional trends that may shape the future of dairy cattle breeding include the development of proprietary genomic evaluations by commercial companies, which may compete with and challenge national and international evaluation systems. More recently, there has been a shift toward isolationist policies and market restrictions (e.g., tariffs) in various countries and country blocks around the world, which threatens the international data collaboration essential for developing complex future traits.

In summary, we envision that dairy herds will exhibit reduced variability in the breeds represented, with a likely predominance of Holsteins, unless global initiatives are undertaken to preserve and enhance the sustainability of smaller breeds—an essential investment for the long-term sustainability of the dairy sector. The dairy cow of the future is expected to be healthier, more resilient, and more fertile, with improved adaptability to precision technologies such AMS. Future cows will be of more moderate size, demonstrate greater feed and environmental efficiency, produce higher levels of milk solids with finer composition, and live longer, while carrying fewer deleterious or unfavorable alleles.

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Notes

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Nonstandard abbreviations used: AMS = automated milking systems; BV = breeding value; HO = Holstein; JE = Jersey; RFI = residual feed intake.

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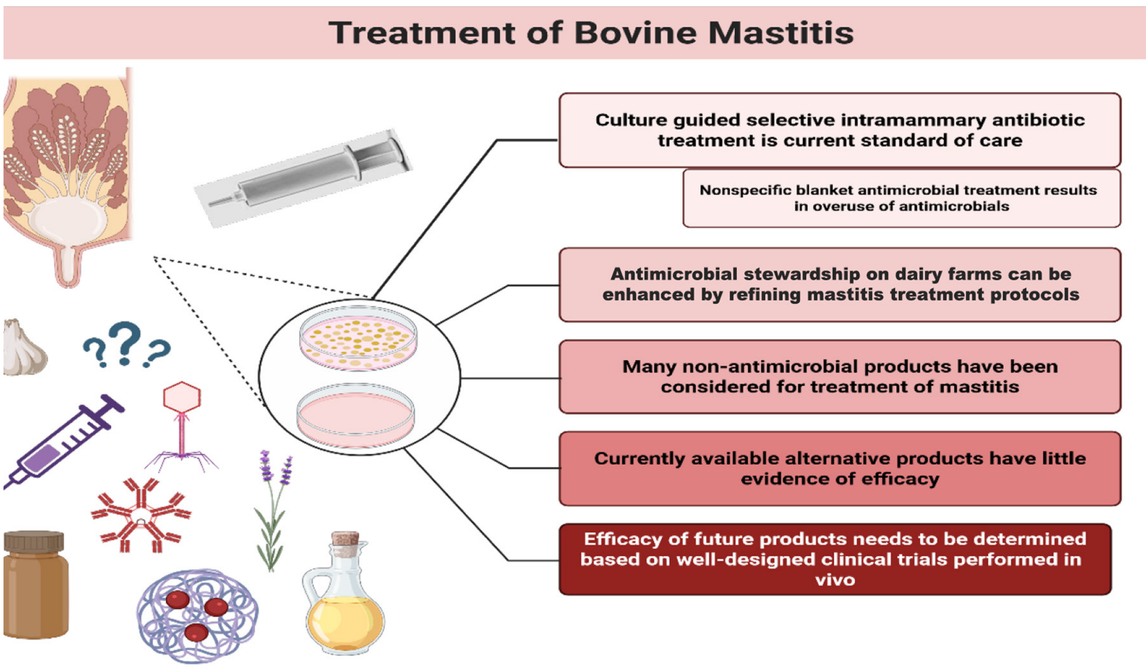
Invited Review
Health, Welfare, and Behavior

The future of udder health: Antimicrobial stewardship and alternative therapy of bovine mastitis

Pamela L. Ruegg*

Graphical Abstract



Summary

Mastitis is usually caused by bacterial infections of the udder, and most cases are currently treated using intramammary antimicrobials. Producers can reduce antimicrobial usage by adopting pathogen- and cow-specific selective treatment protocols. Several non-antimicrobial treatments are available, and researchers have described additional treatment options. Most alternative treatments lack efficacy data. Well-designed clinical trials performed in cows with naturally occurring mastitis are needed to determine the efficacy of alternative products. Graphical abstract created in BioRender (https://BioRender.com/t11r742).

Highlights

- Many farms can reduce dependence on the use of antimicrobials for mastitis treatment.
- Improved stewardship includes the use of culture-guided selective treatment protocols and reduced duration of antimicrobial treatments.
- Improved stewardship includes the use of selective dry cow therapy when possible.
- There is little evidence to support the efficacy of most non-antimicrobial treatments.
- Research to define in vivo efficacy of alternative therapies for mastitis is needed.

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The list of standard abbreviations for JDSC is available at adsa.org/jdsc-abbreviations-25. Nonstandard abbreviations are available in the Notes.

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Invited Review
Health, Welfare, and Behavior

The future of udder health: Antimicrobial stewardship and alternative therapy of bovine mastitis

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Abstract: Although antimicrobial usage is highly restricted in dairy cows, concerns about development and dissemination of resistant bacteria have led to a reexamination of mastitis therapies. In the past, almost all cases of clinical mastitis were treated symptomatically using intramammary antibiotics, and in many regions, most cows received intramammary antibiotic treatments at dry-off. On modern dairy farms, changes in the distribution of etiological agents have reduced the need to give antimicrobials for all mastitis cases. Culture-guided selective treatment protocols for nonsevere clinical mastitis have been adopted on many farms and align with principles of antimicrobial stewardship. Although some antimicrobial therapy is needed to maintain udder health, antimicrobial therapy is not effective or not necessary for resolution of many cases of mastitis. As the use of antimicrobials has declined, many alternative treatments have been explored, but few non-antimicrobial treatments have documented efficacy. The purpose of this paper is to review the concepts of antimicrobial stewardship on dairy farms from the US perspective, with an emphasis on current and future management strategies for udder health.

In veterinary medicine, antimicrobial stewardship (**AMS**) is defined as systematic, proactive actions taken by veterinarians to preserve effectiveness and availability of antimicrobials (AVMA, 2018). On dairy farms, most antimicrobials are used to treat and prevent mastitis (Leite de Campos et al., 2021), so AMS programs must emphasize evidence-based treatment protocols for mastitis (Ruegg, 2022). Mastitis is defined as inflammation of the mammary gland and almost always occurs due to IMI, but many cases do not require antibiotic therapy during lactation. An understanding of the etiologies, the expected effectiveness of the immunological response to IMI and the costs associated with treatment are required to be able to assess the necessity and cost-effectiveness of therapy. Most IMI are caused by bacteria, although algae, yeasts, and other pathogens (including some strains of highly pathogenic avian influenza) have been associated with mastitis. After IMI is established, a nonspecific immune response results in inflammation that is used to detect and characterize the presentation. Subclinical mastitis (**SCM**) occurs when IMI results in an inflammatory response but the milk and udder remain normal in appearance. Detection of SCM is based on measuring the influx of neutrophils and is usually defined when the SCC of milk from individual quarters exceeds 200,000 cells/mL. At the herd level, bulk tank SCC is often used as an indicator of SCM, and values for US herds indicate considerable progress in controlling SCM. From 2000 to 2024, average bulk tank SCC declined from 326,000 to 181,000 cells/mL (CDCB, 2025), and based on monthly SCC values of cows tested by DHIA, the average prevalence of SCM in US herds has declined to ~15%. However, the prevalence of SCM often increases with parity, and at the end of lactation, approximately half of cows in parity 3+ may have SCC values indicative of SCM. If the bulk tank SCC remains acceptable to the processer (usually <400,000 cells/mL), milk from cows with SCM is legal to sell. To limit financial losses due to discarded milk after treatment and to enhance bacteriological clearance, most treatments of SCM are performed at dry-off using intramammary (**IMM**) antimicrobials.

Clinical mastitis (**CM**) is detected by observation of visible changes in milk, with or without changes in the udder and cow. Abnormal milk is the only clinical sign for ~50% of CM cases, whereas ~35% also have inflamed udders and 5% to 15% of cows with CM are systemically ill (Ruegg, 2025). Clinical mastitis is the most frequently recorded disease of dairy cows and occurs in ~20% to 40% of lactations, with greater incidence in multiparous cows (USDA, 2016). Milk that appears abnormal cannot be sold for human consumption (NCIMS, 2023) and must be discarded (or fed to calves), so it has limited or no value. Historically most CM cases were treated nonspecifically using IMM antimicrobials in the hope that treatment would hasten return to saleable milk, although recent research does not support that theory (Ruegg, 2025).

As producers have adopted effective preventive practices, the distribution of etiologies has changed, and many cases are caused by pathogens that are spontaneously cured or are outside the spectrum of activity of approved antimicrobials (Table 1). In many regions mastitis caused by *Streptococcus agalactiae* is rare and in some regions relatively few IMI are caused by *Staphylococcus aureus*. When developing treatment protocols, it is important to recognize that the distribution of etiologies vary between CM and SCM. Culture-negative milk samples account for ~25% to 35% of CM cases. Most culture-negative cases of CM have achieved spontaneous bacteriological clearance before detection and have an excellent prognosis without antimicrobial therapy (Fuenzalida and Ruegg, 2019b). Although many milk samples obtained from quarters with SCM (high SCC) are also culture-negative, the failure to

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The list of standard abbreviations for JDSC is available at adsa.org/jdsc-abbreviations-25. Nonstandard abbreviations are available in the Notes.

Table 1. Distribution of etiologies for clinical and subclinical mastitis

Item	Oliveira et al., 2013	Levison et al., 2016	Fredebeul-Krein et al., 2022	Rowe et al., 2020	McDougall et al., 2022	Niemi et al., 2025
Location	Wisconsin, United States	Ontario, Canada	Germany	United States	New Zealand	Finland
Herds (n)	50	59	65	7[1]	44[2]	12[3]
Case type	Clinical	Clinical	Clinical	Subclinical	Subclinical	Subclinical
Cases (n)	622	936	854	1,078[4,5]	704[4]	260
No growth (%)	27.3	19.6	20.3	74.6[6]	33	75.1
Coliform (%)	33.1	11.5	22.2	2.3	<1	1.5
Streptococci and Strep-like organisms[7] (%)	13.6	14.6	29.9	8.4	18.8	21.5
Staphylococcus aureus (%)	2.8	7.9	4.8	1.0	37.6	8.9
NAS and corynebacteria (%)	6.1	21.7	9.1	74.1	30.8	68.0
Other organisms and mixed (%)	17.1	24.7	13.7	14.2	12.8	0

[1]All quarters of 1,275 cows cultured 2 d before dry-off.

[2]Only California Mastitis Test–positive quarters from cows with SCC >500,000 cells/mL were cultured.

[3]Quarters of cows with last test-day SCC >100,000 cells/mL were PCR tested 0 to 4 d before dry-off.

[4]Culture-positive quarters only.

[5]Culture-positive quarters enrolled.

[6]Of 5,100 quarters cultured.

[7]Includes non-*agalactiae Streptococcus* spp., *Lactococcus* spp., and *Enterococcus* spp.

culture bacteria from those quarters does not always indicate that they are healthy. Chronically increased SCC in culture-negative quarters can occur because the inflammatory response has reduced the number of bacteria to below laboratory detection limits (usually 100 cfu/mL), and these IMI are often caused by pathogens that are nonresponsive to therapy. When bacteriological clearance occurs (either spontaneously or due to effective treatment), the SCC of affected quarters will gradually return to <200,000 cells/mL, but the time required to return to normal varies with etiology and may exceed 4 to 6 wk (Ruegg, 2025). In contrast, with or without bacteriological clearance, milk from cows with CM usually returns to a normal appearance within 3 to 5 d after detection of the case as the inflammatory process resolves. Thus, it is difficult for producers to discern the effectiveness of treatments, as clinical signs and SCC values can be misleading.

A large variety of organisms have been identified from milk of cows with clinical and subclinical mastitis (Kurban et al., 2022). Among culture-positive cases on farms in North America, gram-negative bacteria are commonly recovered from CM, whereas most SCM cases are caused by gram-positive pathogens (Table 1). Recognition of this difference is vital because culture-guided, selective treatment protocols for CM emphasize use of antimicrobials primarily for treatment of cases caused by gram-positive pathogens (de Jong et al., 2023). At dry-off, the low prevalence of SCM caused by gram-negative pathogens (Rowe et al., 2020) indicates that narrow-spectrum IMM antimicrobials are appropriate when dry cow antimicrobial therapy is used. For both CM and SCM, principles of AMS suggest that use of narrow-spectrum IMM antimicrobials that target gram-positive bacteria are appropriate for routine treatment protocols and the broad-spectrum antimicrobials and injectable antimicrobials should be used only for selected cases with defined etiologies (Nobrega et al., 2020).

In most developed countries, antimicrobial usage (**AMU**) on dairy farms is highly restricted due to concerns about food safety and in order to reduce the potential dissemination of resistant bacteria and genes that may pose a risk to public health. Fewer antimicrobial classes and routes are approved for treatment of mature dairy cows, as compared with other food animals. Based on concerns about antimicrobial resistance, some regions have highly restricted use of some antimicrobials (Kuipers et al., 2016; Roy et al., 2020). Several studies have shown that IMM treatments account for most doses of antimicrobials used on dairy farms (Pol and Ruegg, 2007; González Pereyra et al., 2015; Leite de Campos et al., 2021) but this route comprises a very small proportion of the total mass of antimicrobials sold for use in food animals in the United States. The US Food and Drug Administration (**FDA**) summarizes annual sales of medically important antimicrobials approved for use in cattle, swine, turkeys, and chickens by species, year, and route (FDA, 2023). In 2023, of the >6 million kg of antimicrobials sold for use in food animals, antimicrobials designated for cattle (beef and dairy are reported together) accounted for 41% of the total. However, 93% of the total mass of antimicrobials sold were administered through feed or water. Although sulfadimethoxine can be given orally as a treatment of foot rot, bacterial pneumonia, or shipping fever, administration of medically important antimicrobials to adult dairy cows in the United States in feed or water is prohibited. Most cases of CM and SCM are treated using IMM antimicrobials, which are small, fixed doses as compared with other routes. Of the total antimicrobial mass sold for use in food animals in the United States, <0.01% was labeled for IMM administration, indicating that AMU for treatment of mastitis in dairy cattle accounts for a minute proportion of the total antimicrobials sold for use in food animals.

Reviews of trends in antimicrobial resistance of mastitis pathogens from Canada and the United States have concluded that major mastitis pathogens demonstrate only limited resistance to IMM antimicrobials (Barlow, 2025), although other regions with less restrictive AMU regulations have reported more resistance (Li et al., 2023). A recent systematic review of the public health risks posed by antimicrobial resistant genes (**ARG**) in milk concluded that "considering a low percentage of contaminated milk samples, unknown ARG concentrations, and an unproven role in human disease, the risk attributed to ARG in milk seems to be exaggerated by far. However, the risk of ARG selection on farm, resulting in low treatment success in cattle, is a real one and should be met by prudent use of antibiotics" (Sievers et al., 2025, p. 4508). Although the mass of antimicrobials used to treat mastitis is small, AMU varies considerably among farms, and many farmers can reduce AMU and treatment costs (Leite de Campos et al., 2023, 2024) by modifying mastitis treatment protocols. Enhancing AMS must be focused on encouraging veterinarians and dairy producers to use antimicrobials only when necessary and to use narrow-spectrum antimicrobials when possible. Current and future mastitis treatment protocols will need to emphasize reduced reliance on antimicrobials, especially classes that are critical for the treatment of human diseases.

The current standard of care for CM includes review of severity, etiology, and cow characteristics before prescription of antimicrobials (Ruegg, 2025). Severe cases require immediate therapy, including fluids, anti-inflammatories, and both injectable and IMM antimicrobials. Fortunately, most CM is nonsevere, and many cases achieve spontaneous bacteriological clearance without the need for antimicrobials. When possible, culture-guided therapy should be used to guide treatment of nonsevere CM (de Jong et al., 2023). In most instances, IMM antimicrobials are recommended when CM is caused by gram-positive organisms but are not recommended for CM that is culture-negative nor caused by most gram-negative organisms (Nobrega et al., 2018; Fuenzalida and Ruegg, 2019a). Typical management of cases caused by pathogens with high expectations of spontaneous cure involves monitoring cow health and discarding milk until it returns to a normal appearance. Antimicrobials are not recommended for chronic cases (especially *Staph. aureus*; Barkema et al., 2006) or those that are caused by bacteria outside the spectrum of approved IMM antimicrobials. These cases should be managed to prevent transmission by using segregation, dry-off of chronically affected quarters, or culling. Although researchers have not demonstrated that use of nonsteroidal anti-inflammatory drugs (**NSAID**) consistently improve outcomes of nonsevere CM cases (Latosinski et al., 2020), when the udder is inflamed, NSAID administration should be considered to manage pain. Based on common etiologies, few cases of CM on most dairy farms will benefit from treatment with broad-spectrum IMM antimicrobials (Nobrega et al., 2020). Similarly, a recent review concluded that use of parenteral antimicrobials should be restricted to justifiable cases, such as cows affected with severe mastitis, and that treatment of nonsevere CM should be preferentially performed using noncritically important first-generation cephalosporins rather than critically important antimicrobials such as third-generation cephalosporins (Barlow, 2025). If determination of etiology before treatment is not possible, treatment with a narrow spectrum IMM antimicrobial for the shortest labeled duration is suggested. Cow factors should also be considered before using antimicrobials. Successful elimination of IMI has been associated with age, stage of lactation, negative energy balance, history of previous cases, and environmental factors such as heat stress (Dahl, 2018). With or without antimicrobial therapy, younger cows and cows without a history of subclinical IMI have greater odds of achieving bacteriological clearance and fewer recurrences. Based on principles of AMS, longer-duration therapy cannot be recommended for routine treatments because most cases will not benefit (Ruegg, 2025), and unnecessary AMU is not socially or economically justifiable. When routine treatment protocols exceed labeled minimums for IMM antimicrobials, reducing the duration of treatment should be considered as part of applying AMS on dairy farms.

Several researchers have demonstrated that financial benefits of treatment during lactation are based on balancing the cost of discarded milk with factors that influence the probability of cure (Steeneveld et al., 2007; Steeneveld et al., 2011). Unless waste milk is pasteurized and fed to calves, is rarely cost-effective to treat SCM during lactation, but producers should be aware of potential risks of residues in waste milk to calf health(Pereira et al., 2014). In most instances, both efficacy and economic impact indicate that treatment of SCM is most effective when IMM antimicrobials are given at dry-off.

Administration of IMM antimicrobials in every quarter of each cow that dries off is termed blanket dry cow therapy (**bDCT**). In North America, bDCT became popular in the 1970s due to the high prevalence of quarters affected by SCM. In other regions, selective dry cow therapy (**sDCT**) based on use of IMM antimicrobials only to treat apparently infected quarters was the standard of care (Rajala-Schultz et al., 2021). As the prevalence of SCM has declined in North America, use of sDCT has been promoted (Rowe et al., 2025). Selective dry cow therapy programs promote use of IMM antimicrobials only in cows with existing IMI, and new infections are prevented by use of non-antimicrobial teat sealants. Adoption of sDCT usually results in a 40% to 50% reduction in AMU and in appropriate herds can be used without affecting udder health (McCubbin et al., 2022). Herds that consider sDCT should have bulk tank SCC <250,000 cells/mL and use an appropriate method to identify cows that will benefit from IMM antimicrobials. A simple algorithm that based treatment decisions on occurrence of an individual monthly SCC >200,000 cells/mL or ≥1 case of CM in the ending lactation has been shown to be effective (Rowe et al., 2021). Retrospectively applying this algorithm to records from >35,000 cows in 37 herds, ~51% of cows would not have required antimicrobial therapy (Leite de Campos et al., 2024), thus indicating considerable potential for reducing AMU. However, based on those criteria, almost 60% of cows in the third or greater lactation would have required antimicrobials, and parity should be considered when using sDCT programs. Use of sDCT is an example of the application of AMS and should be encouraged for herds that meet selection criteria. However, inappropriate herd or cow selection can result in reduced udder health that may require additional antimicrobial treatments (Niemi et al., 2025), so it is important for veterinarians and dairy producers to carefully consider decisions about sDCT on a herd-specific basis.

Mastitis is usually caused by bacteria, and when treatments are indicated for nonsevere cases, antimicrobials remain the drug of choice. Global emphasis on reducing AMU and a desire to provide non-antimicrobial therapies for organic dairy cows has stimulated interest in non-antimicrobial products. Some alternative products (such as anti-inflammatories) do not have antimicrobial activity but may reduce the severity of clinical signs or stimulate immune responses. Other alternatives are novel products with putative bactericidal or bacteriostatic abilities, and the commercial availability of such products varies among countries. Several alternative therapies, including acoustic pulse therapy, quorum sensing boluses, herbal IMM products, and an ozonated food-grade vegetable oil are sold in the United States and have subtle or overt claims for efficacy as mastitis treatments, although none have been FDA ap-

Table 2. Types of alternative therapies for mastitis included in selected published reviews

Compound	Francoz et al., 2017	Li et al., 2023	Morales-Ubaldo et al., 2023	Debruyn et al., 2025
Anti-inflammatories	X	X	X	X
Acoustic pulse therapy		X		X
Bacteriophages		X		
Essential oils	X		X	X
Homeopathy	X		X	X
Nanotechnology		X	X	
Peptides		X	X	X
Phytotherapy	X	X	X	X
Polymers			X	
Probiotics		X		
Others	X	X	X	X

proved for this purpose. To date, none of these alternative products have had efficacy documented by independent, controlled clinical trials, and the proposed mechanisms of action suggested for these products remain speculative. Producer testimonials are often provided as evidence of efficacy, but should be viewed cautiously, as pathogen specific outcomes are needed to determine efficacy, and resolution of clinical signs or modest reductions in SCC are not good indicators of achievement of bacteriological clearance.

Identification of efficacious, non-antimicrobial treatments aligns with goals of AMS to reduce AMU on dairy farms. However, a systematic review of currently available alternative treatments was not encouraging (Francoz et al., 2017). Treatments included anti-inflammatories (including flunixin, dexamethasone, prednisone, carprofen, ibuprofen, ketoprofen and others; n = 14 studies), oxytocin (n = 5), biologics (including immunoglobulins and hyperimmune serums; n = 9), homeopathy (n = 5), botanicals (including herbs and aroma therapy; n = 4), probiotics (n = 2) and others (ascorbic acid and riboflavin; n = 2). Bacteriological and clinical cure were the primary outcomes, although the authors noted that most studies had considerable risk of bias and low power to detect differences. Endotoxin challenges were used in most trials that evaluated anti-inflammatories, so results of these studies were focused on alleviation of clinical signs in cows experiencing severe gram-negative mastitis. Some studies did not include either positive or negative controls, and a few did not perform statistical analyses. Although the authors noted that deficiencies in study designs prohibit definitive conclusions for many treatments, they concluded that several treatments (homeopathy, oxytocin with or without frequent milk out, or probiotics) could not be recommended based on lack of evidence of efficacy. The recommendation against probiotics is further supported by a comprehensive review (Rainard and Foucras, 2018) that concluded "there was no sound scientific foundation for the use of probiotics to prevent or treat mastitis" (p. 1). Francoz et al. (2017) noted the urgent need for additional well-designed clinical trials that provide evidence-based recommendations for non-antimicrobial treatments for mastitis.

Several other reviews and numerous research papers have evaluated a variety of potential alternative candidates for treatment of mastitis (Table 2; Rainard and Foucras, 2018; Li et al., 2023; Morales-Ubaldo et al., 2023; Debruyn et al., 2025). Competitive exclusion using organisms such as NAS have been shown to have the potential to inhibit growth of mastitis pathogens (Caddey et al., 2025) and may have potential as a topical treatment to prevent mastitis (Rainard and Foucras, 2018). Unfortunately, most of the proposed treatments have been evaluated only based on their ability to inhibit bacterial growth of selected organisms in vitro and lack evidence of how the compounds behave in vivo or against naturally occurring mastitis cases. The mechanism of action for many of the proposed treatments remains speculative, and additional research is needed to develop practical and effective therapies (Li et al., 2023). Few alternative products have been evaluated using controlled trials and some potential products such as bacteriophages and plant-based products are known to interact with or degrade in milk (Debruyn et al., 2025). Study designs vary among compounds and very few have been adequately powered. Commercial viability of future treatments will require much more rigorous studies that result in sufficient evidence of efficacy to justify costs of the official regulatory processes in various countries. Thus, results of evidence-based studies are needed before the role of alternative therapies for mastitis in AMS programs can be defined.

Treatment of mastitis accounts for the majority of AMU on dairy farms. Current and future treatment protocols should be based on knowledge of etiology with the principle of using antimicrobials in a targeted fashion only when indicated. There is considerable opportunity to improve AMS by limiting AMU to cases in which cows will benefit from their use and by using the shortest possible duration of treatment. There is currently little data to support use of most alternative treatments, and resolution of clinical signs should not be used as an indication of efficacy. Use of non-antimicrobial therapies should be supported by scientific evidence that the treatments enhance clinical and bacteriological outcomes in a cost-effective manner. Although treatment of mastitis using antimicrobials is indicated for some cases, bacteriological clearance of many pathogens will occur spontaneously. The development of mastitis results in reduced cow welfare and financial losses. Rather than promoting unproven alternative therapies, our emphasis should be focused on methods to better prevent IMI including development of effective vaccines. Current and future advances in treatment of mastitis should be based on data from well designed, pathogen specific, negatively controlled clinical trials.

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Notes

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Nonstandard abbreviations used: AMS = antimicrobial stewardship; AMU = antimicrobial usage; ARG = antimicrobial resistant gene; bDCT = blanket dry cow therapy; CM = clinical mastitis; FDA = US Food and Drug Administration; IMM = intramammary; NSAID = nonsteroidal anti-inflammatory drug; SCM = subclinical mastitis; sDCT = selective dry cow therapy.

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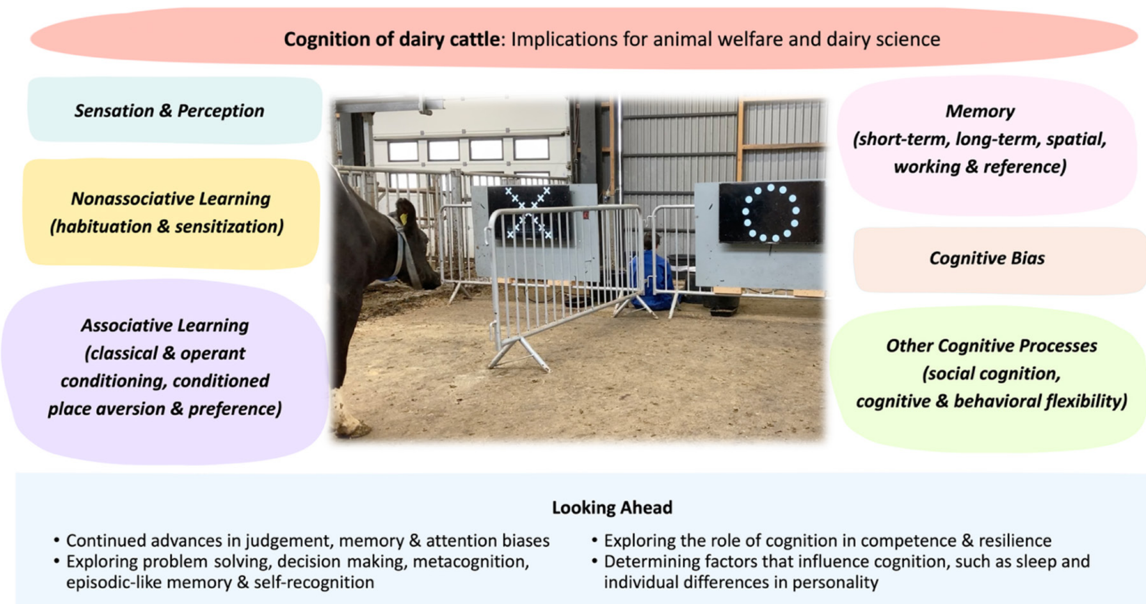
Invited Review
Health, Welfare, and Behavior

Cognition of dairy cattle: Implications for animal welfare and dairy science

Kathryn L. Proudfoot,[1]* Thomas Ede,[2] Catherine L. Ryan,[3] and Heather W. Neave[4]*

Graphical Abstract

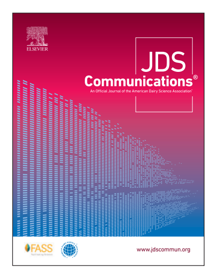


Summary

Understanding how dairy cattle perceive, retain, and respond to information from their caretakers and the environment has received growing interest from researchers over the past several decades. The aims of this review are to explore what we currently know about dairy cattle cognition and how it relates to their welfare, as well as highlight knowledge gaps to stimulate future research. Photo by Heather W. Neave and Margit Bak Jensen: Dairy cow in an active choice judgment bias task, Danish Cattle Research Centre, Aarhus University, Denmark.

Highlights

- Dairy cattle cognition is a growing area of research with implications for welfare.
- Cattle show complex perception, learning, and memory.
- Cognitive and behavioral flexibility allows cows to adapt to different environments.
- Further research is encouraged to explore the role of dairy cow cognition in animal welfare.



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The list of standard abbreviations for JDSC is available at adsa.org/jdsc-abbreviations-25. Nonstandard abbreviations are available in the Notes.

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Cognition of dairy cattle: Implications for animal welfare and dairy science

Kathryn L. Proudfoot,[1]* Thomas Ede,[2] Catherine L. Ryan,[3] and Heather W. Neave[4]*

Abstract: The study of dairy cattle cognition has gained increasing attention over the past several decades, offering insights into the relationship between cognition and animal welfare. The objectives of this narrative review are to summarize a selection of studies exploring different cognitive processes in dairy cattle, discuss how these processes relate to common management practices and animal welfare, and identify knowledge gaps to guide future research. We begin with a brief overview of research into how dairy cattle perceive and sense the world around them, followed by a description of different types of learning and memory studied in dairy cattle, including nonassociative and associative learning, as well as short- and long-term memory. We then discuss how researchers have explored cognitive processes in dairy cows to understand their social lives, their ability to cope with challenges, and how they feel under different management conditions. Continued research into dairy cattle cognition is encouraged, including both foundational studies asking questions about the cognitive abilities of dairy cattle, as well as applied questions that can lead to improvements to their housing and management. We end by offering several avenues of future research into the cognition of dairy cattle, including a better understanding of competence and resilience, factors that influence cognition such as sleep and individual differences, as well as other under-investigated topics, such as problem-solving and metacognition.

The study of dairy cattle cognition has emerged as a growing area of scholarly interest over the last several decades (e.g., see reviews: Rørvang and Nawroth, 2021; Neave, 2025). Cognition, or the ability to "acquire, process, store, and act on information from the environment" (Shettleworth, 2010, p. 4), is an essential survival tool for animals, allowing them to make quick adaptations to their changing environments and circumstances. Recognizing and understanding the cognitive abilities of animals can provide insight into their emotional (affective) states, which is a core component of their welfare (Fraser et al., 1997). Franks (2018) proposes that the relationship between cognition and welfare is bidirectional: Cognition can affect animal welfare (e.g., providing cognitively enriching environments can improve affective states), and animal welfare can influence cognition (e.g., animals experiencing negative affective states may show hindered learning abilities).

To date, research on dairy cattle cognition has advanced our understanding of their cognitive abilities and revealed opportunities to improve their care (e.g., see detailed review by Rørvang and Nawroth, 2021). As research in this field continues to evolve, the goal of this short narrative review is to encourage further discussion and interdisciplinary research in dairy cattle cognition. The specific objectives are to summarize a selection of studies exploring different cognitive processes in dairy cattle, discuss how these processes relate to common management practices and animal welfare, as well as identify knowledge gaps to guide future research.

A starting point for understanding cognition in dairy cattle is how they perceive and sense the world around them. Knowledge about cattle sensation (e.g., the sensory input, including sight, smell, touch, taste, hearing) and perception (i.e., the brain's interpretation of that input) can help us design appropriate experiments, environments, and handling procedures. For example, dairy cattle can discriminate between features of their environment such as colors, shapes and smells (reviewed by Rørvang and Nawroth, 2021), which can be used to create effective paradigms to assess animal learning. In some cases, cows may fail to learn a task simply because we do not understand what they can and cannot perceive. This phenomenon is relevant across dairy science, as a cow's response to an experimental intervention may be affected by cues that the researcher may be unaware of (e.g., shadows, smells). Further research is encouraged to determine how basic sensation and perception in cattle can facilitate the design of environments and experiments that are meaningful, promote positive experiences, and minimize stress-inducing stimuli.

Researchers have also explored different types of learning and memory in dairy cattle and how these can provide insight into their welfare. For example, dairy cattle have demonstrated habituation, a basic form of nonassociative learning that does not rely on the ability to make associations between stimuli. Habituation occurs when an animal's response to a repeated stimulus decreases over time, as the animal learns that the stimulus is nonthreatening. For example, Kutzer et al. (2015) exposed heifers to milking procedures for 10 d before calving and found that, compared with control animals, the habituated heifers showed fewer steps and kicks after calving during milking, and many showed a decline in flight distance to human handlers.

Dairy cattle also experience the other form of nonassociative learning, sensitization, whereby animals may become more reac-

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tive to a repeated presentation of a stimulus, such as dairy cows being more sensitive to repeated loud noises at auction (Lanier et al., 2000). Predicting whether an animal will habituate or sensitize to a stimulus is difficult, but in general, animals tend to habituate when the stimulus is of low to moderate intensity and sensitize to more intense stimuli (Domjan, 2015). According to Domjan (2015), habituation and sensitization are both important mechanisms of emotional modulation; pleasure, fear, exploratory motivations, and aggression can all be modified by these fundamental learning mechanisms. Further studies on nonassociative learning in dairy cattle are encouraged to explain and reduce behavioral reactivity to new environments and handlers.

Dairy cattle also exhibit associative learning, such as classical (Pavlovian) and operant conditioning, which require cattle to make associations between 2 stimuli. For classical conditioning, an animal associates a neutral stimulus with a stimulus (an unconditioned stimulus) that naturally provokes a response (an unconditioned response). For example, in a study of virtual fences, Verdon et al. (2021) trained cows to associate a tone to a brief electrical pulse to provoke the cows not to enter a restricted area of pasture; cows soon learned to avoid the restricted areas after hearing the tone alone. Lee et al. (2018) suggest that virtual fences may provide greater predictability and control than traditional electric fences for animals that learn to associate the tone with the electric pulse. However, animals that fail to learn this association may face increased welfare risks due to reduced predictability and control. Although not well studied in dairy cattle, classical conditioning can also modify emotional, endocrine, and immunological responses in animals, such as taste-immune associative learning in rodents (reviewed by Hadamitzky et al., 2020). Thus, there remain several opportunities for further exploration of classical conditioning and its role in dairy cattle welfare.

For operant conditioning, the likelihood that a cow performs a specific behavior is either increased (reinforcement) or decreased (punishment) based on its consequences, such as adding a stimulus (positive) or removing a stimulus (negative). Research on this concept in dairy cattle has been mainly focused on positive reinforcement, such as training dairy cows to enter automated milking systems by rewarding them with grain (Jacobs and Siegford, 2012) and training heifers to stand still for an injection (Lomb et al., 2021). Positive reinforcement training may have several benefits to cattle, as it has been shown to elicit play behaviors in heifers, suggesting that the animals find the training itself rewarding (Heinsius et al., 2024), and may also play a role in more positive relationships between cattle and their caretakers. In contrast, although not well-studied in dairy cattle, researchers caution the use of punishment as a training tool; although punishment can be effective at stopping an unwanted behavior, it can also result in fear (Casey et al., 2021).

Researchers have also used paradigms of associative learning to more directly understand affective states in cattle. For example, conditioned place aversion tests have been used to determine if dairy cattle associate their surroundings with a negative experience. Ede et al. (2019) showed that dairy calves will avoid an area with visually distinct cues (red squares vs. blue triangles) if they had been associated with hot-iron disbudding compared with a sham procedure. Conditioned place aversion has been further applied to explore length of transportation (Creutzinger et al., 2022), social buffering (Nogues et al., 2023), and hunger (Lafon et al., 2024) in cattle. Both conditioned place aversion and its counterpart, conditioned place preference, are promising areas for further research in dairy cattle.

In addition to understanding how cattle acquire new information, researchers have also studied their memory (how they store, retain, and retrieve this information) to guide future behavior (Shettleworth, 2010). Researchers typically study one of 2 characteristics of cattle memory: what is remembered (e.g., a location), and the duration of the memory. For example, with sufficiently high initial food motivation and gradual learning, cows can solve a complex maze and remember it for up to 6 wk (Hirata et al., 2016). Calves previously loaded into trailers with the aid of sugar cubes were easier to load and showed fewer stress indicators 5 wk later (Fukasawa, 2012). Similarly, heifers exposed to brushing and haltering early in life were less reactive in tests of fearfulness involving humans, suggesting memory of at least 6 mo of positive handling (Boissy and Bouissou, 1988). A recent pilot study noted that heifers remembered multiple tasks, such as coming when called or touching a target, for up to a year after their training (de Boyer des Roches et al., 2025).

Cattle also display multifaceted spatial memory (i.e., using information from within and across trials), believed to improve foraging efficiency (Laca, 1998). This idea has been tested in calves by adapting the hole-board test using bottles baited with milk among empty bottles, assessing calves' working memory (avoiding milk bottles already visited during a test session) and their reference memory (learning to return to locations where food was found in previous sessions; Lecorps et al., 2022). Decreasing calves' milk allowance (from 12 L/d to 6 L/d) led to a decline in memory in the hole-board test, likely driven by feelings of hunger (Lecorps et al., 2023). Together, these studies on cattle memory demonstrate the complex and long-term memory of dairy cattle, the link between affective states and memory, and the value of building long-lasting positive relationships between humans and animals.

As herd animals, dairy cattle lead rich social lives that require them to recognize, adapt to, and learn from others in the group, collectively referred to as social cognition. Dairy cattle can discriminate between conspecifics (Suchon et al., 2025) and can tell the difference between individual cattle using their faces alone (Coulon et al., 2011). However, familiarity of the conspecific may affect speed of learning, and not all individuals learn to discriminate between unfamiliar conspecifics (Suchon et al., 2025).

Social learning, a component of social cognition, occurs when individuals acquire new behaviors or information by observing or interacting with others. This differs from social transmission, where conspecifics influence existing behaviors, such as through social facilitation (increased behavior in the presence of others) or local and stimulus enhancement (increased attention to certain objects or locations). Such processes can help naïve animals navigate novel environments more efficiently by relying on the experiences of others (Bandura, 1977). Both social transmission and social learning influence behavior in many farmed species, but evidence for social learning in cattle is limited. Only one study has directly tested this: Stenfelt et al. (2022) found that observer cows did not outperform controls that did not observe a demonstrator cow complete a spatial task, suggesting reliance on individual rather than socially acquired information.

Social cognition also extends to how cattle recognize, remember, and modify their responses to their human caretakers. For example, researchers have shown that cows are capable of distinguishing between people (Munksgaard et al., 1997; Rybarczyk et al., 2001). Although the specific cues that cattle use remain unclear, it is likely that a combination of clothing, faces, or height play a role. Munksgaard et al. (1997) found that cows can also associate specific people with aversive handling; cows kept a greater distance from people who had previously subjected them to negative handling (strikes on the head with open palm) compared with those who had previously provided positive interactions (food and petting). Cows have also been shown to remember people who handled them using aversive techniques. For example, Rushen et al. (1999) showed that cows had increased heart rate and more residual milk after milking when a person who had previously handled them negatively was present in the milking parlor compared with a person who had previously handled them gently. More research on the possible benefits of positive interactions between cattle and their caretakers is warranted.

Dairy cattle have also been shown to exhibit cognitive and behavioral flexibility, or the ability to adapt responses when environmental conditions change (Uddin, 2021). Cognitive flexibility refers to the mental capacity to adjust information processing or decision-making strategies, whereas behavioral flexibility describes the ability to modify actions accordingly. This flexibility is typically assessed using reversal learning tasks and intra- or extradimensional shifts (e.g., changes to previously learned T-shaped mazes). Reversal learning tasks have been used to evaluate how housing and management of dairy calves affect their cognitive functioning. For example, calves raised with their dams or peers performed better on a reversal task compared with individually housed calves, suggesting that social contact early in life improves cognitive flexibility and adaptability (Gaillard et al., 2014; Meagher et al., 2015). Similarly, dietary improvements, such as access to hay, improved calves' performance in a T-maze when the rewarded arm changed (reversal task) or when an object was unexpectedly placed in the rewarded arm (intramaze shift task; Horvath et al., 2017). Calves that succeeded in these types of tasks also showed smoother integration into new social groups after weaning, highlighting how cognitive flexibility may lead to improved social adaptability (Horvath and Miller-Cushon, 2018).

Other cognitive processes that have received little or no attention in cattle include problem solving and decision making. Tasks that test for these processes have been developed for other farm animals, which could be drawn upon for application in dairy cattle. For example, the Pig Gambling Task has pigs choose between small, more frequent rewards versus larger but less frequent rewards, which tests cognitive and emotional processes related to decision making, impulse control and risk assessment (van der Staay et al., 2017). "Impossible" tasks have been used to investigate how animals respond when a previously solvable task becomes unsolvable; animals must first learn to solve the task, but the test trial assesses their subsequent behavior (e.g., attention to or interaction with the human experimenter) once the solution is no longer possible. In farm animals, this task has often focused on human–animal communication or social referencing rather than problem solving itself (e.g., in goats; Langbein et al., 2018). Detour tasks also test an animal's problem-solving ability and inhibitory control by needing to navigate around a transparent or opaque barrier (i.e., temporarily move away from the reward) to reach a visible reward (Nawroth et al., 2016), with only one such test performed in dairy cows to our knowledge (Stenfelt et al., 2022). Adapting tasks that have been developed in other species will allow us to better understand these abilities in dairy cattle and their implications for welfare.

Researchers are increasingly recognizing that an individual's cognitive function is heavily influenced by their affective state; thus, measuring differences or changes in cognitive function can be a way of indirectly evaluating how the animal feels under different management conditions. In the past decade, cognitive bias tasks have emerged as a promising method to evaluate how emotion influences information processing (Mendl et al., 2009). The most common approach, judgment bias, measures how animals interpret ambiguous cues by training them to associate one cue with a positive outcome (e.g., a reward) and another with a negative outcome (e.g., no reward or a mild punishment). Once trained, animals are presented with ambiguous, intermediate cues to assess whether they respond as if expecting the positive or negative outcome; these responses are interpreted as optimistic or pessimistic, and positive or negative emotional states, respectively.

Cognitive bias paradigms have been applied to understand the affective states of dairy cattle under different conditions. For example, calves were pessimistic following disbudding (Neave et al., 2013) and dam separation (Daros et al., 2014), suggestive of a negative emotional state, and were optimistic when pair-housed versus individually housed (Bučková et al., 2019), suggesting a positive emotional state. However, cows did not show the expected optimism when housed on pasture (Crump et al., 2021) or an enriched indoor housing (Kremer et al., 2021) despite being motivated for these conditions. Attention bias (differential attention toward threatening or rewarding stimuli, depending on emotional state) has also been explored in dairy cows with mixed results (Franchi et al., 2020; Kremer et al., 2021). However, memory bias (differential recall of positive and negative memories, depending on emotional state; see Burman and Mendl, 2018) has never been explored in dairy cattle to date. In general, cognitive bias tests offer valuable insight into affective states by drawing upon an understanding of how emotions affect the way we think and process information.

As the field of animal welfare continues to evolve, there is a growing need for further applied and basic scholarly work that advances our knowledge about the cognitive abilities of dairy cattle and enhances our understanding of their welfare. For example, cognitive approaches have the potential to play a pivotal role in advancing the emerging field of positive animal welfare, which recognizes that the promotion of positive experiences, rather than merely mitigating negative ones, is critical for an animal to have a good life (Rault et al., 2025). Within this framework, researchers are currently exploring effective ways to study animal competence (i.e., their ability to effectively interact with and respond to their environment) and resilience (i.e., their ability to maintain or recover mental and physical functioning when faced with challenges). Continued research into cognitive and behavioral flexibility, as well as problem solving and decision making, will provide important insights into how dairy cattle learn to navigate complex aspects of their environment across different life stages.

Research is also needed to understand factors that influence cognition in dairy cattle, such as sleep and individual differences in personality. For humans and laboratory animals, researchers have shown that sleep organizes newly acquired information, consolidates memories, and improves attention, learning, habituation to emotional stimuli, cognitive flexibility, and problem solving (Palmer et al., 2024). Although we understand some basics about sleep in dairy cattle (Proudfoot and Ternman, 2024), research is encouraged to explore how sleep and sleep loss affect cognitive performance in cattle. Moreover, exploring individual differences in processing information and solving problems is another key avenue for future work. There is evidence that individual cows develop different strategies for cognitive tasks, including basic processes such as habituation (Paranhos da Costa et al., 2021). Identifying and linking cognitive strategies to personality in cattle will also help us build a more comprehensive view of how individuals cope with challenging environments.

The research to date has scratched the surface of understanding the cognitive abilities of dairy cattle. A further step is the exploration of more complex processes, such as metacognition (thinking about one's own thinking), episodic-like memory (recalling the "what," "when," and "how" of an experience), or self-recognition (the ability to recognize one's own self). Each of these processes are experimentally and theoretically challenging but have been explored in other mammalian species (e.g., Crystal, 2010). Evidence of such processes in nonhuman animals has shifted scientific and ethical perspectives on animal minds, highlighting the need for environments and management practices that reflect and support their cognitive and emotional capabilities (Nawroth et al., 2019). These emerging areas of inquiry have the potential to deepen our understanding of how dairy cattle experience their own learning, recall and emotionally process past experiences, and respond to the affective states of conspecifics. Future work might combine behavioral approaches with novel techniques, such as noninvasive neuroimaging, electrophysiological measures, or pharmacological approaches, to investigate these complex cognitive processes in cattle.

Overall, current research demonstrates that dairy cattle possess complex cognitive abilities, including sophisticated learning, memory retention, as well as cognitive and behavioral flexibility. Although we have much more to learn, recognizing and understanding these abilities has important implications for anyone who works with dairy cattle, including the farmers who care for them, dairy scientists using them in their research, and animal welfare scientists seeking to improve their welfare.

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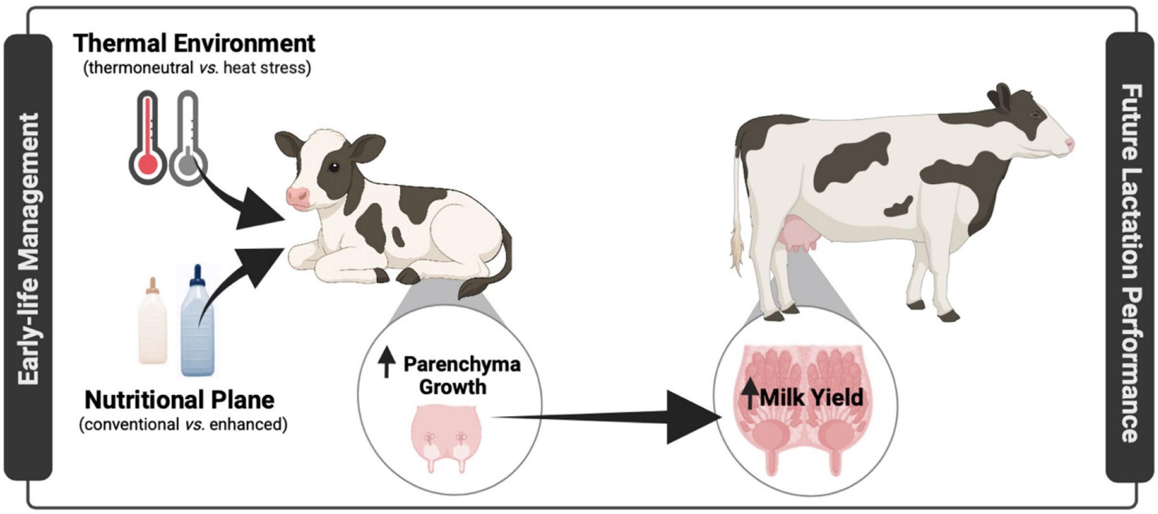
Invited Review
Physiology

Making future udders: Mammary development and perinatal programming of dairy cattle

Jimena Laporta* and Maverick C. Guenther

Graphical Abstract



Summary

The last 2 months before birth and the first 2 months after birth represent a crucial window for organ development, including the mammary gland, in dairy cows. Traditionally, it was thought that allometric mammary growth began after weaning or around puberty. However, recent research indicates that significant early development of the mammary parenchyma occurs during the perinatal period and can influence a cow's future milk production. This early growth is highly sensitive to environmental and nutritional factors. Heat stress abatement and higher nutritional planes in early life increase mammary parenchyma growth and improve future productivity. Proper management during the perinatal period is essential to optimize lifetime milk yield.

Highlights

- The perinatal period is a critical window for mammary parenchymal development.
- Early-life heat abatement and enhanced milk nutrition promote parenchyma growth.
- Environmental and nutritional factors can program future lactational performance.

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The list of standard abbreviations for JDSC is available at adsa.org/jdsc-abbreviations-25. Nonstandard abbreviations are available in the Notes.

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Making future udders: Mammary development and perinatal programming of dairy cattle

Jimena Laporta* and Maverick C. Guenther

Abstract: The perinatal period, described herein as the time spanning the final 2 mo of gestation through 2 mo postnatal, is a critical window of developmental plasticity for many organs in placental mammals, including the mammary gland (MG). In dairy cattle, early-life MG development involves foundational morphogenic events that are highly sensitive to environmental and nutritional factors. Emerging evidence challenges the long-standing belief that substantial MG development begins after weaning and lasts until puberty, showing instead that preweaning mammary parenchymal (mPAR) growth is allometric and its degree of development can influence future lactational capacity. Overall BW typically doubles from birth to 60 d, whereas both whole udder weight and the mammary fat pad increase by ~2.2 to 3 times over the same period. In contrast, the mPAR exhibits pronounced allometric growth, expanding 15 to 35 times during this time. Early-life management strategies, such as heat abatement to maintain thermal homeostasis and enhanced nutrition through higher milk intake supporting greater average daily gain, further promote mPAR development and can positively influence future lactation performance of dairy cows. These findings underscore the importance of integrating developmental biology into heifer-rearing strategies and emphasize the need for precise environmental and nutritional management during this critical window to support lifelong mammary function and optimize herd performance.

Perinatal programming—the concept that environmental conditions during critical windows of early development can shape long-term physiological outcomes—has become a foundational principle in developmental biology. This concept was first recognized in humans through the epidemiological work of David Barker linking poor maternal nutrition during the Dutch Hunger Winter to adult-onset of cardiovascular disease (Barker, 1990). Since then, this idea has expanded into the animal science field. Strong evidence now supports that the late gestation and early postnatal period—collectively referred to herein as the perinatal window—represents a critical time of developmental plasticity. Developmental plasticity during this time allows the fetus and neonate to adjust their physiology, metabolism, and organ development, anticipating the postnatal environments or adjusting to the current environment conditions, respectively. This adaptive capacity helps them optimize the allocation of resources to support survival, growth, and the functional maturation of key organ systems. Developmental plasticity adaptations are driven by intricate interactions between environmental cues, such as temperature, nutritional status, and perceived stressors, which influence gene expression patterns that regulate the growth, development, and functional differentiation of organs (Bell and Greenwood, 2016).

Adverse in utero conditions, including maternal nutrient restriction and hyperthermia, can alter normal fetal growth trajectories, often resulting in asymmetric development that prioritizes critical organs like the brain over peripheral tissues in various livestock species (Reynolds et al., 2023; Laporta and Skibiel, 2024). Although developmental adaptations to insults may enhance short-term survival, they often come at a cost, potentially leading to decreased immune competence, suboptimal growth, and reduced productivity later in life. Following birth, the early postnatal period, particularly the first 2 mo of life, remains a highly plastic developmental window during which several organ systems are still maturing and therefore susceptible to environmental and nutritional influences. In livestock species, immune, metabolic, endocrine, and exocrine organs continue rapid structural and functional development during this early life phase. Adverse external factors—such as undernutrition, thermal stress, and pathogen exposure, among others—have been shown to program lasting physiological and structural outcomes in dairy cattle and other species. For example, lack of colostrum ingestion is linked to poor maturation and development of the gastrointestinal tract (Pyo et al., 2020). Additionally, postnatal heat stress negatively affects development by impairing liver homeostasis, altering mammary gland (**MG**) growth, reducing milk yield, and affecting survivability to the first lactation (Guenther et al., 2025; Laporta et al., 2025).

In contrast, specific stimuli can help mitigate early-life stressors and support healthier developmental trajectories of key tissues and organs. Growing evidence in livestock species demonstrates that the early-life environment can epigenetically and physiologically program animals leading to positive long-term phenotypic effects (Laporta et al., 2022; Vautier and Cadaret, 2022). When these conditions are favorable, such as through adequate heat abatement interventions to maintain thermal homeostasis, developmental adaptations can promote optimal organ maturation, enhance metabolic efficiency, and induce beneficial epigenetic modifications (Laporta et al., 2025) that may be stable until adulthood (Skibiel et al., 2018). In line with this, an adequate nutrient supply (higher planes of nutrition) during critical development windows leads to epigenetic alterations that change gene expression (Vailati-Riboni et al., 2018), and these changes may persist and influence long-term physiology (Loor, 2022). These physiological and molecular

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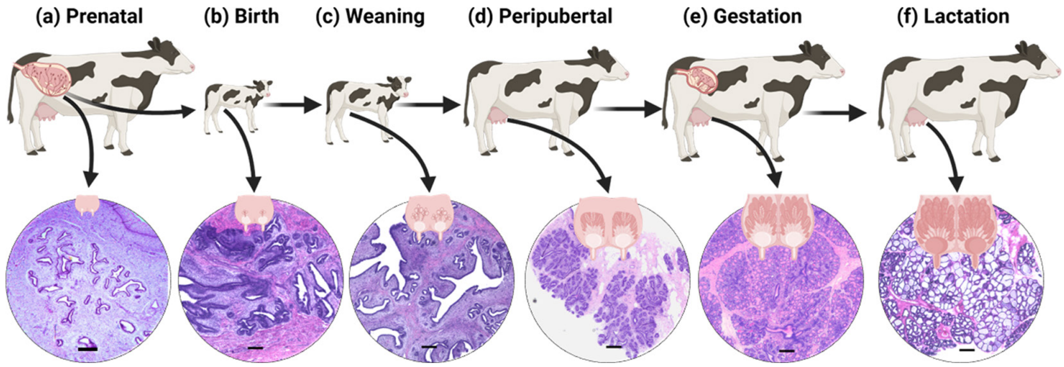

Figure 1. Major longitudinal macro- and microstructural development of the bovine mammary gland from the prenatal period to first lactation. Mammary development begins prenatally (in utero; a) and progresses postnatally through key stages: (b, c) preweaning (birth to 2 mo), (d) postweaning to puberty (~2–13 mo), (e) gestation (~13–24 mo), and (f) first lactation (~24–34 mo). Ductal growth is initiated during the perinatal period (−2 to +2 mo relative to birth), although functional alveoli have not yet formed. This critical developmental window establishes the mammary fat pad, parenchymal mass, and the initial epithelial-ductal architecture, laying the structural foundation for future mammary growth, differentiation, and lactation performance. Representative hematoxylin and eosin-stained sections of mammary tissue shown at (a) the prenatal stage (150 d of gestation; scale bar = 200 μm; Hara et al., 2018; reproduced from Hara et al., J. Vet. Med. Sci. [2018]. ©Japanese Society of Veterinary Science. Licensed under CC BY-NC-ND 4.0.); (b, c) birth and weaning (4 h of life and 63 d of age; scale bar = 500 μm; Dado-Senn et al., 2022); (d) peripubertal stage (12 mo of age; scale bar = 500 μm; Davidson et al., 2025); (e) gestation (6 mo pregnant; scale bar = 500 μm, J. Laporta, unpublished); and (f) lactation (42 DIM; scale bar = 500 μm; Skibiel et al., 2018).

changes ultimately prepare the animal for improved health, greater resilience to stress, and enhanced productivity, underscoring the lasting influence of early-life conditions on long-term performance.

A key organ of immense relevance to the dairy industry and the primary focus of this review is the MG. The bovine MG undergoes a sustained period of development and uniquely experiences phases of growth and regression across the animal's lifetime (Hurley and Loor, 2011; Akers, 2017). Although the majority of its functional growth takes place postnatally, MG development begins much earlier (in utero) and continues through the early preweaning phase before reaching the pubertal, gestational, and lactation phases of development characterized by substantial systemic endocrine changes (Figure 1). Mammary growth and development across these different stages can be characterized by macrostructural changes, such as udder enlargement driven by mammary fat pad (**mFP**) expansion, as well as microstructural changes, such as lobulo-alveolar growth and differentiation within the mammary parenchyma (**mPAR**). Notably, macrostructural growth without proper microstructural maturation would result in a gland that appears developed but lacks the cellular foundation to support lactation. Understanding early-life mammary growth and its susceptibility to environmental factors during the perinatal period offers an opportunity to refine management strategies that optimize lifetime milk yield.

Each developmental stage of the MG plays a critical role in shaping a heifer's future milk production potential. Specifically, prenatal mammary development begins early in gestation with the formation of the mammary line and bud at ~35 and ~45 d of gestation, respectively (Akers, 2002). These structures continue development throughout fetal life with elongation and branching of primary and secondary ducts (Hara et al., 2018). At birth, the MG consists of an immature mPAR with rudimentary ductal epithelial systems which are encased in stromal tissue. This mPAR structure will begin to invade the surrounding mFP. These early morphogenic events establish the architecture of the gland for future development (Knight and Sorensen, 2001). Historically, the preweaning period—from birth to ~8 wk of age—was considered a relatively inactive phase for mammary development, with growth believed to occur isometrically, at the same rate as overall body growth. This view was based on studies that assessed the whole gland macrostructure and DNA or RNA content as proxies for growth. However, recent studies using immunohistochemistry and gene expression analysis on specific tissue types have revealed substantial microstructural and molecular changes during this period.

Although studies during this early developmental stage are still limited, key findings have demonstrated that mPAR volume increases markedly, with up to a 60-fold increase from 30 to 90 d of age (Akers et al., 2005). Based on ultrasound measurements, a 6-fold increase in the cross-sectional area of mPAR from wk 1 to wk 8 of life was reported (Esselburn et al., 2015). In a recent study, we euthanized and dissected udders of Holstein heifers at birth, revealing a 25-fold increase in mPAR mass from birth to 63 d of age, compared with 2.1- and 2.3-fold increases in the mFP and whole udder, respectively (adapted from Dado-Senn et al., 2022; Figure 2). This mPAR growth far exceeds the 2.2-fold increase in BW, highlighting the allometric nature of development during this time. Moreover, epithelial and stromal cells in the mPAR exhibited substantially higher proliferation rates at birth and weaning compared with early lactation mammary tissue (Figure 3). The rapid growth of the MG at this time is influenced by a complex interplay of systemic and locally produced hormones including estrogen, growth hormone, and IGF (Akers 2017). These findings underscore the biological importance of the preweaning period in establishing mammary developmental potential, highlighting that any perturbations during this critical period may disrupt the foundational growth and proliferation processes. After weaning through puberty, the whole gland undergoes continued allometric growth. Estrogen and progesterone promote ductal elongation, branching, and early alveolar development. The most profound transformation occurs during gestation, with synergistic effects of estrogen, progesterone, and prolactin stimulating lobulo-alveolar proliferation. These changes culminate in lactogenesis at parturition, driven by hormonal shifts (Tucker, 2000). The degree of mammary development at calving determines peak yield and lactation persistency (Capuco and Choudhary, 2020), making these times of early development a key determinant of lifetime productivity.

Environmental and nutritional conditions experienced by dairy heifers during the perinatal period can exert long-term effects on future production capacity by programming gene expression patterns that shape the developmental trajectory of the MG. Early-life hyperthermia during the perinatal period can impair the growth and maturation of the MG due to the disruption of hormonal signaling, cell proliferation, vascular development, and epigenetic programming that normally occur in a thermoneutral environment. Specifically, prenatal heat stress during the final 2 mo of gestation leads to lighter calves with reduced mFP and mPAR at birth, independent of birth weight (Dado-Senn et al., 2021, 2022). Ductal structures in prenatally heat-stressed calves are underdeveloped at birth and remain smaller with substantially less branching at weaning. Although mPAR mass (in terms of size and weight) recovers by weaning, the mFP pad does not, potentially limiting subsequent mPAR invasion and impairing further mammary development (Dado-Senn et al., 2022). Cell proliferation within ductal epithelium is essential for mammary tissue expansion, as it drives the growth and elongation of the ductal network. Notably, heat stress in utero reduced cell proliferation by ~50%, indicating persistent morphogenic impairments that are evident at birth and weaning (Dado-Senn et al., 2022). However these reductions also extend into puberty and the first lactation, with reduced lobulo-alveolar development and a 25% to 30% lower mammary epithelial cell proliferation rate in glands of prenatally heat-stressed heifers (Skibiel et al., 2018; Davidson et al., 2025). Ultimately, heat stress exposure during the late stages of fetal life derails mammary development, leading to lasting microstructural changes in the MG that result in lower synthetic capacity at maturity (Monteiro et al., 2016; Laporta et al., 2020). Conversely, providing heat abatement to pregnant cows during hot summer months allows late stages of gestation to occur under thermoneutral conditions, which has been shown to reverse the detrimental effects triggered by in utero hyperthermia on postnatal whole body and MG development (Davidson et al., 2025). Specifically, heifers born to cool dams have larger udders with a 2-fold increase in the mPAR mass at birth, with restored cell proliferation when assessed longitudinally (Dado-Senn et al., 2022; Davidson et al., 2025). By preserving mPAR growth during late gestation, prenatal heat abatement supports long-term mammary function and enhances lifetime milk production (Laporta et al., 2020).

Thermoregulation of neonatal mammals, including calves, is immature at birth, rendering them particularly susceptible to environmental heat stress, which may perturb hormonal and metabolic pathways that affect the MG. Although direct studies specifically examining postnatal heat stress during the first months of life and its long-term impact on MG development in livestock species are limited, evidence from our group supports that preweaning heat stress in dairy calves alters MG development (Guenther et al., 2025). Ongoing studies are investigating the long-term effects of preweaning heat stress to understand if these changes lead to decreased milk production in adulthood. Briefly, preweaning heat stress exposure in Holstein dairy heifers results in the development of disproportionately larger udders harvested at 63 d of age, driven by an expansion of the mFP rather than mPAR tissue. Despite similar overall mPAR weight and size compared with thermoneutral counterparts, calves exposed to heat stress exhibit significantly reduced cellular proliferation within the mPAR, an essential process for ductal and lobulo-alveolar development, potentially compromising later stages of mammary development and their future milk-producing capacity (Guenther et al., 2025). This evidence underscores the critical importance of managing stressors in early life, ultimately promoting mammary health and optimizing lifelong lactational performance.

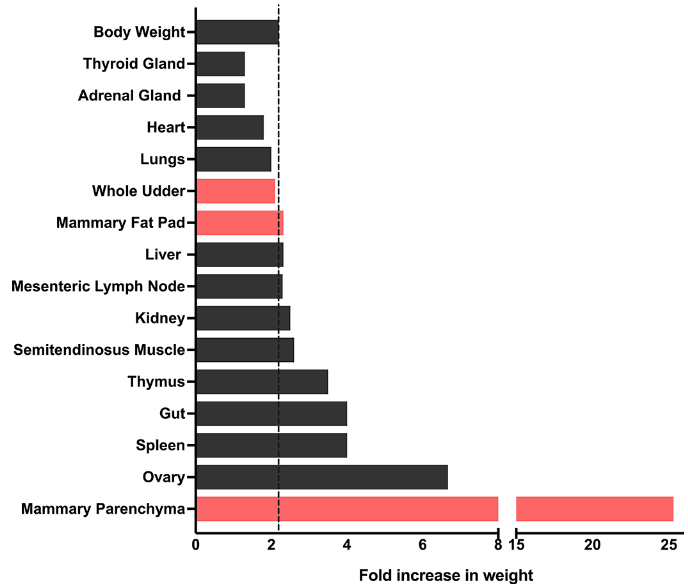

Figure 2. Body and organ growth from birth to weaning in Holstein heifers. The dotted vertical line represents the change in live BW during the preweaning period (0–63 d of age, 2.2-fold increase). Bars illustrate the change in absolute organ weight (Dado-Senn et al., 2021) over the preweaning period, with pink bars denoting mammary gland components (whole udder, mammary fat pad [mFP], and mammary parenchyma [mPAR]; Dado-Senn et al., 2022). The mPAR demonstrates pronounced allometric growth (25-fold increase), whereas the whole udder and mFP exhibit isometric growth (2.1–2.3-fold increase), proportional to BW. These findings emphasize the disproportionate expansion of the epithelial-rich mPAR relative to other mammary and extra-mammary tissues during early postnatal development.

Historically, rearing strategies have prioritized rapid growth at minimal cost to minimize the nonproductive lifespan of heifers, often at the expense of optimal organ development. However, this paradigm is beginning to shift as evidence is accumulating in favor of more biologically appropriate, nutrition-focused management approaches that support long-term productivity. Enhanced nutrition during the preweaning period—particularly increased milk or milk replacer intake—supports greater ADG and stimulates mammary development. Comparisons across studies providing different planes of nutrition in early life can be challenging, as some studies alter the level of milk allotment (Daniels et al., 2009; Soberon and Van Amburgh, 2017; Niwińska et al., 2022), milk replacer composition (Meyer et al., 2006), or both allotment and composition (Brown et al., 2005; Daniels et al., 2009; Geiger et al., 2016). However, across the previously noted studies, which harvested and

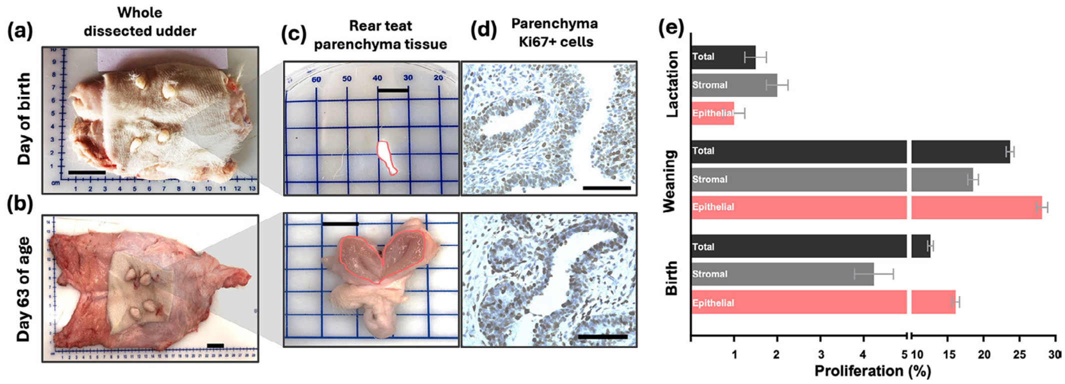

Figure 3. Mammary gland development from birth to weaning and proliferation at birth, weaning, and lactation. Gross morphology of the whole dissected udder was assessed (a) 4 h after birth and (b) at 63 d of age (scale bars = 2.4 cm). (c) Representative images of mammary parenchyma (mPAR) dissected from the region proximal to the rear teat (scale bars = 1 cm). At 63 d, the mPAR was bisected and the teat was left for visual reference. (d) Corresponding immunohistochemistry images showing Ki67$^+$ (brown) cells, used to assess epithelial cell proliferation (scale bars = 100 µm). (e) Quantification of epithelial (pink bars), stromal (gray bars), and total (black bars) proliferative index (% Ki67$^+$ cells) in mPAR tissue at birth, weaning (0 and 63 d of age; Dado-Senn et al., 2022), and early lactation (21 DIM; Skibiel et al., 2018). The average total proliferation indices were 13%, 24%, and 1.5%, respectively. Data are presented as mean ± SEM.

dissected mPAR tissue around weaning, enhanced planes of nutrition result in a 2.3- to 6-fold increase in mPAR mass with a 1.1- to 1.4-fold increase in BW. Enhanced nutritional input during the preweaning phase has also been associated with increased mammary epithelial cell proliferation and increased mammogenic hormone receptor abundance within the mPAR (Geiger et al., 2017). Additionally, an enhanced plane of nutrition during the preweaning period increases circulating IGF-I (Rosadiuk et al., 2021), which has been implicated as a key hormone for MG development (Akers et al., 2000). This demonstrates that despite the differences in feeding management across studies, mPAR tissue is highly responsive to improved nutrition during this critical developmental window.

Although a clear knowledge gap remains regarding the early postweaning period and its influence on mammary development and future lactation performance, meta-analyses have linked preweaning enhanced ADG to improvement in first-lactation milk, protein, and fat yield (Soberon and Van Amburgh, 2013; Jiang et al., 2025). More specifically, each additional kilogram of preweaning ADG was associated with ~1,550 kg more milk in the first lactation (Soberon and Van Amburgh, 2013). In a separate meta-analysis, studies supported the notion that higher preweaning ADG (0.6–1.0 kg/d) significantly increased 305-d milk, fat, and protein yield, with the strongest positive associations with first-lactation performance observed as ADG approached the upper end of this range (Jiang et al., 2025). Interestingly, starter DMI showed no significant associations with any first-lactation performance metrics (Jiang et al., 2025). Together, these findings underscore the critical importance of early-life nutrition in determining not only overall growth, but also the developmental trajectory of key tissues like the MG leading to improved lactation.

In summary, this review provides evidence that mPAR development is allometric, highly proliferative, and developmentally plastic during the perinatal period, and that this initial growth phase may be critical in shaping future lactational capacity. Despite growing evidence in support of early-life management influencing MG development, few controlled long-term studies link these changes to future lactation, limiting our ability to assess lasting impacts. Our rapidly evolving understanding underscores the need for science-driven, proactive heifer-rearing strategies that recognize the long-term implications of early-life exposures. Optimizing environmental and nutritional conditions during these sensitive windows of development will likely improve productivity, resilience, and welfare in future dairy herds.

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Notes

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Nonstandard abbreviations used: mFP = mammary fat pad; MG = mammary gland; mPAR = mammary parenchyma.

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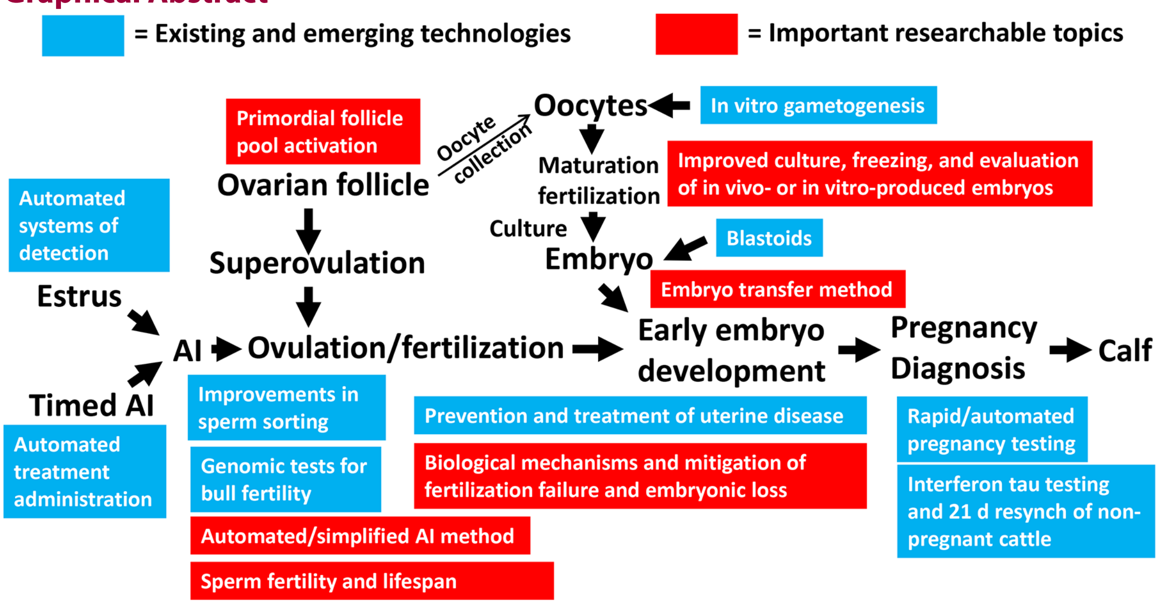
Invited Review
Physiology

The intersection of biology and advanced technologies defines the future of dairy reproductive management

M. C. Lucy*

Graphical Abstract

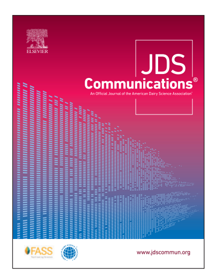


Summary

The past 25 years have been a period of rapid improvement in dairy reproduction through the implementation of new technologies that were unknown a short time ago. The next 25 years will likely be similar, with the refinement of existing technology and the development of new technology to address current challenges to dairy reproduction. Many of these new developments will address the need for greater on-farm automation, necessitated by the consolidation of farms (more cows per farm) in the face of shortages in large animal veterinary and agricultural labor. Despite important advances in new technology, there are also important questions and researchable topics that need to be addressed so the field of dairy reproduction can advance. The collective result of new knowledge and new technology will drive further improvements in genetics, fertility, and the efficiency of reproduction in high-producing dairy cattle.

Highlights

- New technology will address current challenges to dairy reproduction.
- Consolidation (larger farms) will lead to a greater reliance on automation.
- Improvements will be made to existing technologies.
- Emerging technologies have the potential to effect major changes.
- Important questions and researchable topics need to be addressed.



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The list of standard abbreviations for JDSC is available at adsa.org/jdsc-abbreviations-25. Nonstandard abbreviations are available in the Notes.

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Invited Review
Physiology

The intersection of biology and advanced technologies defines the future of dairy reproductive management

M. C. Lucy*

Abstract: Advances in reproductive management in dairy cattle have typically been made through the application of new technology. The past 25 yr have been a period of rapid improvement in dairy reproduction through the implementation of new technology that was unknown a short time ago. The next 25 yr will likely be similar with the refinement of existing technology and development of new technology to address the current challenges to dairy reproduction. Many of these new developments will address the need for greater on-farm automation necessitated by the consolidation of farms (more cows per farm) in the face of shortages in large animal veterinary and agricultural labor. Genomics will continue to play an important role in improving fertility on farm. There is the possibility that postpartum uterine health could benefit from advanced technologies that are emerging as effective treatments for tissue damage caused by disease. The reprogramming of somatic cells into gametes (in vitro gametogenesis) or embryos (blastoids) may entirely change the methods used to propagate elite genetics from female animals. Despite important advances in new technology, there are also important questions and researchable topics that need to be addressed so that the field of dairy reproduction can advance. These include automating or simplifying the current method of artificial insemination, addressing the short lifespan of sperm in the reproductive tract, and solving fertilization failure and embryonic loss following insemination. Embryo technologies await new discoveries to improve embryo yield from donor animals, increase the development of embryos in culture, reduce the damage caused by freezing embryos, and effectively evaluate embryo quality before transfer. The collective result of new knowledge and new technology will drive further improvements in genetics, fertility, and the efficiency of reproduction in high-producing dairy cattle.

A lot has changed in dairy reproductive management since the publication of "Reproductive loss in high-producing dairy cattle: Where will it end?" 25 yr ago (Lucy, 2001). Examples of reproductive technologies that were not routinely practiced or known at the time of the 2001 publication include Ovsynch and its subsequent iterations (Presynch, Ovsynch, double Ovsynch, Resynch, and so on; Fricke and Wiltbank, 2022); genomics and genomic selection for reproductive traits (Lucy, 2019); sex selection of spermatozoa (Seidel, 2014); and pregnancy diagnosis using blood or milk (Ott et al., 2025). These new technologies were introduced and expanded into the dairy industry to reverse the negative reproductive trends that existed in the early 2000s. The present-day dairy industry faces a new set of challenges to efficient reproduction that include larger herds and fewer agricultural workers per farm (Lucy and Pohler, 2025). The next 25 yr in bovine reproduction will inevitably prove to be equally remarkable to the previous 25 yr with respect to the technologies that are developed and implemented on farm. In 1981, Dr. Thomas E. Starzl, the father of organ transplantation, wrote "what was inconceivable yesterday, and barely achievable today, often becomes routine tomorrow" (Eghtesad and Fung, 2017, p. e2). The thoughts of Dr. Starzl are clearly applicable to the reproductive technologies used on dairy farms. The objective of this narrative review is to assess the present-day status of reproductive research and associated technologies on dairies and highlight the "barely achievable" technologies that may become "routine" on tomorrow's farms. Existing and emerging technologies (Table 1), as well as research topics for the future (Table 2), are presented.

The current focus for estrus detection is the development of more sensitive wearable electronic technology. The primary means of detection is an accelerometer and in some cases location sensors that measure animal movement (Cerri et al., 2021). The addition of a rumination sensor improved the sensitivity of detection because cows in estrus eat and ruminate less (Beauchemin, 2018). There is also the possibility of the detection of estrus through body temperature monitoring (rumen bolus, ear tag, or vaginal implant; Reith and Hoy, 2018). Remote systems for estrus detection have the added benefit of detecting sick cows that also eat and ruminate less, are less active, and have elevated body temperature. Wearable devices fit into the need for greater on-farm automation to address a reduced agricultural labor force (Lucy and Pohler, 2025). Increased sensitivity will likely be achieved through an improved understanding of estrus behavior (movements, social interactions, and so on) and the collection of additional data on individual cows that may not be linked to their movement or rumination (Cerri et al., 2021). It is very likely that data (health, reproduction, milk production, BCS, and so on) from wearable and other remote sensing devices as well as genomic testing will be combined so that health and reproductive programs are tailored to the benefit of fertility in the individual cow ("targeted reproductive management"; Giordano et al., 2022; Bruinjé and LeBlanc, 2024; Chebel et al., 2025).

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Table 1. Expectations for existing and emerging technologies to increase reproductive success in dairy cattle

Existing technologies	Emerging technologies
• Greater sensitivity and specificity for estrus detection systems based on activity, location, and novel behaviors indicative of estrus. • Alternative methods for the administration of $PGF_{2\alpha}$ and GnRH treatments in timed AI systems including robotic arms, needle-free systems, and automated intravaginal delivery. • Further improvements in the sorting efficiency and fertility of sex-selected semen. • Development of highly sensitive genomic tests to predict field fertility of AI sires • Automation of in-parlor milk sampling and analysis for the purpose of pregnancy diagnosis based on milk pregnancy-associated glycoproteins (PAG). • Further development of methods to detect pregnancy based on interferon tau (IFNT) to enable resynchronization of estrus in nonpregnant cows within 21 d after breeding.	• Development of biomarkers in milk (including LH) that complement milk progesterone for estrus detection. • Milk or blood pregnancy testing that competes directly with ultrasound for instantaneous pregnancy diagnosis on farm. • Prevention and treatment of fibrosis and tissue damage caused by infection and uterine inflammation postpartum. • Reprograming damaged uterine tissue using chemical reprograming factors. • In vitro gametogenesis (derivation of fertile oocytes from induced pluripotent stem cells for in vitro fertilization and the production of embryos for transfer). • Blastoids (derivation of large numbers of fertile blastocysts from induced pluripotent stem cells)

The onset of estrus coincides with the LH surge that causes ovulation ~30 h later (De Rensis et al., 2024). If the time of the LH surge is known, then the time of ovulation is known and the detection of estrus is not necessary. The Herd Navigator system (DeLaval, Tumba, Sweden) is an inline milk progesterone monitoring technology consisting of a “biomodel” that signals the milking robot for sample collection from individual cows, an autosampler (for milk collection), and a progesterone analysis unit that measures milk progesterone (Bruinjé et al., 2025). One limitation of the system is that the time of estrus can only be approximated based on the time of luteolysis. This may be explained by the high variability in circulating estradiol before estrus caused by hepatic metabolism of estradiol in high-producing dairy cows (Wiltbank et al., 2011). Using a wearable device for the detection of estrus as well as the Herd Navigator system (milk progesterone analysis) would greatly increase the sensitivity of the estrus detection because false-positive cows (high activity with high progesterone) could be identified and not inseminated. Developing a module for LH surge detection in milk or alternative milk biomarkers for estrus could also be used to pinpoint the ideal time for breeding. Inline near-infrared analysis of milk samples in real time (during milking) could provide an alternative means of detecting reproductive hormones or other reproductive biomarkers in lactating cows (Giannuzzi et al., 2022).

Timed artificial insemination (**AI**) programs circumvented the need for estrus detection (Fricke and Wiltbank, 2022). Most dairies in the United States rely entirely or in part on timed AI programs to achieve acceptable reproductive rates and create the “high fertility cycle” where cows are inseminated and become pregnant at a targeted postpartum interval that is appropriate for the dairy (Fricke et al., 2023). Other than the ethical concerns of repeated intramuscular injections expressed by some and unfounded human food-safety concerns, the only limitation of the timed AI technology is the labor required to identify and treat cows. Using self-locking head locks to “lock up” an entire pen of cows to find and treat a small number of cows reduces milk production of the pen compared with control (Paudyal et al., 2023). Electronic means to identify cows needing treatment as they move through the milking parlor or sort gates in the parlor return alley (or both) provide a means to separate cows efficiently for treatment. Installation of a robotic arm for treatment administration would further reduce the need for farm labor. Needle-free systems could simplify treatment administration and reduce animal stress response (Leslie et al., 2025). The development of a programmable intravaginal device for the delivery of $PGF_{2\alpha}$ and GnRH treatments holds promise to completely automate timed AI programs (Ren et al., 2023). In the meantime, dairies are increasingly combining timed AI with automated estrus detection systems to identify cows in estrus before timed AI and before pregnancy diagnosis to reduce the labor and expense associated with timed AI treatments (Laplacette et al., 2024).

The cervix separates the vagina from the uterine body. This important biological barrier protects the uterine lumen from bacterial or viral infection (Miller, 2024). The cervix also represents the greatest barrier to efficient insemination of cattle that is not easily solved through automation or overcome with new technology. Artificial insemination as it is practiced today is essentially the same as it was practiced over 75 yr ago (Salisbury and Vandemark,

Table 2. Researchable topics with important long-term implications for dairy reproduction

Researchable topics
• Automated or simplified methods for AI. • Factors that affect sperm lifespan in the female reproductive tract and strategies that can be used to increase sperm lifespan to enhance fertility. • Biological mechanisms and mitigation of fertilization failure and embryonic loss following AI. • Mechanisms to stimulate the development of primordial to primary follicles and sustain development to the antral follicle stage for the purpose of improving the number of harvestable oocytes and embryos from individual cattle. • Improvements in the culture of bovine embryos and cryopreservation of bovine embryos and gametes (oocytes and spermatozoa). • New methods to identify high-fertility bovine embryos before transfer and refinements to the transcervical embryo transfer technique to increase the survival of implanted embryos.

1951). The author is not aware of any new technology designed to automate the transcervical AI method. A novel method of semen administration with acceptable fertility would be a welcome innovation to the dairy industry.

The development and implementation of AI as a tool to improve the genetics of dairy cows was revolutionary technology that was enabled by the dilution and storage of semen. Sorting of bovine spermatozoa into X- and Y-chromosome-bearing fractions created a second revolution enabled by new technology (Seidel, 2014). Although progress has been made, preservation techniques for spermatozoa are imperfect with ~50% of cells dying during freezing/thawing and there are inconsistent and unexplained responses to cryopreservation for individual sires (Yánez-Ortiz et al., 2022). These inconsistencies lead to considerable variation in the fertility of sires that ultimately affect the success of AI. "Fresh" semen (not cryopreserved) is routinely used in grass-based dairy production systems because of high semen demand during the breeding season. Fresh semen is loaded at a lower sperm dose per straw (compared with frozen) and can achieve equal fertility. The number of inseminations from a single ejaculate, therefore, can be increased if fresh semen is used (Murphy et al., 2016). Fresh sex-sorted semen loaded at 1×10^6 sperm per straw had similar fertility to conventionally frozen sex-sorted semen loaded at 2×10^6 sperm per straw in both cows and heifers (Maicas et al., 2019). The use of fresh sex-sorted semen instead of cryopreserved sex-sorted semen may further extend the salable units of sexed semen from a single ejaculate and simplify the insemination procedure by eliminating the thawing step.

The task of creating high-fertility sires is made difficult by the fact that the traits of female fertility (typically included in selection indices) and male fertility are not highly correlated. Recent progress in identifying genomic markers for male fertility may hold promise for the identification of high-fertility sires at the embryonic stage when genomic tests are typically done (Peñagaricano, 2024).

Cattle are outliers among animal species with respect to survival of spermatozoa in the reproductive tract (~24 h) with a more typical survival time among species being measured in multiples of days, months, or years (Holt, 2011). If the survival of spermatozoa in the bovine reproductive tract were longer, then the timing of AI could be less precise, perhaps enabling a single insemination several days before ovulation with acceptable fertility. Sperm microencapsulation may extend the lifespan of sperm but has not achieved fertility superior to conventional insemination (Nebel and Saacke, 1994). The fertility of a sire depends, in part, on the lifespan of their sperm in the female tract (Saacke et al., 2000). Identifying the biological mechanisms of sperm survival in the female tract and interceding to increase the sperm lifespan holds great promise for increasing fertility and simplifying reproductive management on farm (Miller, 2024).

Recent studies have demonstrated that the period from ovulation to the entry of the fertilized embryo into the uterus (morula stage embryo; 5 to 7 d after AI) is the time of greatest embryonic loss (Berg et al., 2022; Crowe et al., 2025). The losses during this time (30%) are approximately split between fertilization failure and subsequent developmental failure. Neither fertilization failure nor developmental failure can be satisfactorily explained based on existing knowledge but are entirely consistent with in vitro fertilization where a percentage of oocytes do not fertilize and many fertilized embryos do not develop (Moore and Hasler, 2017). An additional 10% to 15% of embryos die while the embryos develop to the filamentous stage and leading up to maternal recognition of pregnancy. The collective loss from the 2 initial periods of development (fertilization to the initiation of maternal recognition of pregnancy) is 40% and there is minimal understanding of why embryos are lost during this period and no effective strategies to mitigate this loss. The failure to address this loss is in part explained by our inability to easily identify cows that are pregnant or not pregnant during this early period, and this makes the investigation of the associative causes of the embryonic loss difficult to study.

The secretion of interferon tau (**IFNT**) from the embryo as the maternal recognition of pregnancy signal (Johnson et al., 2024) and the formation of placental binucleate cells that secrete pregnancy-associated glycoproteins (**PAG**; Ott et al., 2025) initiate a period where pregnancy can be detected using a chemical test. The PAG provide a slightly earlier result (~28 d after AI) when compared with ultrasound for pregnancy diagnosis that is typically done 32 d after AI. The chemical testing of PAG does not require the skilled labor that is needed for an ultrasound exam. Sample collection and the downstream analyses can be performed on the farm using unskilled labor and the sample analyzed on farm or at central laboratories. The disadvantages of PAG (compared with ultrasound examination) are (1) a PAG test does not provide a cow-side (instantaneous) pregnancy diagnosis that would allow the immediate treatment of nonpregnant cows (typically a $PGF_{2\alpha}$ injection); (2) a PAG test cannot differentiate between a healthy conceptus (with heartbeat) and dead conceptus (present but without a heartbeat); and (3) there is also a long half-life of PAG in the circulation of cows that have undergone embryonic loss (Giordano et al., 2012). Lateral flow tests for PAG provide pregnancy results within 15 to 30 min (marketed by IDEXX [Westbrook, ME] and BioTRACKING [Moscow, ID]). Instantaneous chemical diagnosis of pregnancy like that achieved with a handheld glucose monitor (5 s from sample application to result) is a challenging goal that would require a novel platform for small molecule analysis. Blood sample collection is difficult to automate on farm, but automated milk sampling into a bar-coded vial for individual cows is easily achievable technology. Regardless of the test speed, the ease of automation for milk sampling will likely make PAG milk testing the primary means of pregnancy diagnosis on future dairies.

Measuring IFNT is difficult in blood but circulating leukocytes can be assayed for interferon stimulated genes (**ISG**) including *OAS1*, *MX2*, and *ISG15* (Ott et al., 2025). Sampling cervical or vaginal cells (in lieu of peripheral blood) demonstrated that tissues near the pregnancy have both IFNT and a robust ISG response. Bishop et al. (2025) reported the development of a cervical sampling device and an IFNT ELISA assay that can be used to diagnose pregnancy within 16 d after AI (Bishop et al., 2025). This system allows pregnancy diagnosis and resynchronization of nonpregnant cows before the "natural" return to estrus, which has distinct advantages in dairy production systems (Lucy, 2025).

The final period of major embryonic loss (28 to 60 d of pregnancy) has received considerable attention because the embryonic loss can be measured throughout this period using a combination of chemical pregnancy tests and ultrasound examination (Binelli et al., 2025). Not unexpectedly, the proposed causes of embryonic loss are diverse. Santos et al. (2009) concluded that "factors that reduced conception rate on day 30 after AI also increased pregnancy loss between 30 and 58 d of gestation" (Santos et al., 2009,

p. 207). Whatever factors reduce pregnancies per AI, therefore, do not appear to selectively target different stages of pregnancy up to d 60 when the placenta is fully formed.

Cows with early postpartum uterine disease have lesser fertility later in lactation. This paradigm is similar to that proposed in the "Britt hypothesis" (Britt, 1991). According to the Britt hypothesis, oocytes that initiate their development early postpartum during negative energy balance are damaged and ovulate during the breeding period with a lower fertility. Likewise, uterine disease early postpartum (metritis and endometritis) damages the uterus so that uterine function is compromised (Caldeira et al., 2025) and fertility during the breeding period is lower (~20 percentage points lesser pregnancy per AI at first postpartum AI; Bruinjé et al., 2024). Some of the uterine "damage" is easily recognized including the presence of inflammation and lymphocytic foci (Lucy et al., 2016) as well as adenomyosis and fibrosis (Sellmer Ramos et al., 2025). Fibrosis is typically viewed as an inevitable outcome of tissue damage, but recent studies in humans suggested otherwise where fibrosis (scar tissue formation) can be prevented with the antimalarial drug artesunate (Zhang et al., 2024) or treated with CAR-T cells (Zhang et al., 2025).

"Inflammatory memory" is the process through which inflammation imprints nonimmune cells within the affected tissue to permanently change their function (Naik and Fuchs, 2022). We found evidence for this in a recent study where the uterine transcriptome of cows that were previously healthy or metritis were compared following slaughter ~80 or 165 d postpartum (Silva et al., 2024). The analysis identified a large effect of early postpartum metritis on the uterine transcriptome later postpartum. The metritis had a greater effect on the caruncular endometrium (uterine sites for placental attachment) compared with the intercaruncular endometrium. This specific effect on the caruncular endometrium may explain why placentation fails in cows that previously had metritis. To restore full fertility, it may be necessary to "partially reprogram" uterine cells meaning that epigenetic imprints created by disease are erased so that cells return to a naïve state (i.e., their baseline epigenetic state that was present before being exposed to the inflammatory milieu created by the immune response to uterine disease). Reprograming of cells was traditionally done by transfecting cells with transcription factor genes (*Oct4*, *Sosc2*, *Klf4*, and *Myc*; OSKM; "Yamanaka factors") that were stably integrated into the genome of the host cells. The stable expression of these genes reprogrammed cells to a more stem-like state (Yücel and Gladyshev, 2024). "Partial chemical reprograming" is similar but a chemical cocktail is used in lieu of the OSKM factors (thus avoiding genetic modification of host cells). The partial reprogramming can reverse aging and erase epigenetic marks associated with disease (Cipriano et al., 2024). The new program could restore fertility to an otherwise damaged and infertile uterus.

Genomics will continue to play a large part in the reproduction of future cows. Most modern-day selection indices have a heavy weighting on health, longevity, and fertility. A look into the future is provided by the "Next Gen" study at Teagasc Moorepark (Ireland). In a study that encompassed 5 lactations, the Irish Economic Breeding Index (**EBI**) was tested by comparing cows within the top 5% nationally for the EBI (elite cows) versus cows with the national average (**NA**) EBI (based on genomic testing). The EBI is heavily weighted for fertility (~25%) because seasonal calving herds in Ireland have a requirement for a 1-yr calving interval. Although milk solids production was marginally affected (elite slightly greater than NA), the fertility and survival was greater for elite versus NA with ~60% of elite cows remaining in the herd to 5 lactations compared with ~40% for NA cows. The elite cows had greater BCS and improved metabolic indicators (greater glucose, insulin, and IGF1 and reduced BHB; O'Sullivan et al., 2020). The "stress" of milk production was the same for the 2 groups because the production was almost identical, but the "strain" created by the production (based on glucose, insulin, IGF1, and BHB) was less in the elite. Traditional dairy selection indices with a heavy weighting on milk production created considerable strain through negative energy balance and BCS loss in early lactation (Lucy, 2019). Modern genetic selection indices that achieve similar milk production with less BCS loss and normalized metabolic indicators will benefit the reproduction of future cows.

Superior dairy genetics is generally disseminated through elite sires with a superior genomic test. Compared with males, the superior genetics found in an individual female is vastly more difficult to propagate. Although superovulation or transvaginal oocyte recovery/in vitro embryo production can be applied to females, these procedures have only marginally improved with respect to embryo yield since their inception over 60 yr ago (Moore and Hasler, 2017). Mammals are programed to maintain follicles in a quiescent primordial pool that are released incrementally over time into the growing pool (thus preserving the nonrenewable pool of gametes throughout the reproductive lifespan; Zhao et al., 2021). The failure to improve embryo yield traces back to the yet unsolved problem of how to release a greater number of primordial follicles from the quiescent pool (Picton, 2022). The phosphatidylinositol 3-kinase (PI3K) growth factor pathway is clearly involved in primordial follicle pool activation because oocyte-specific deletion of *Pten* (a negative regulator of the PI3K pathway) led to the activation of primordial follicles and complete depletion of the primordial follicle pool (Reddy et al., 2008). The PI3K pathway is activated by both insulin and IGF1, both of which are closely tied to ovarian follicular development in cattle (Lucy, 2000). Ovarian inactivation of *PTEN* and the large-scale activation of primordial follicles in cattle, however, has not been achieved.

Progress has been made with respect to superovulation as well as the in vitro maturation and fertilization of oocytes and the culture and freezing/thawing of embryos (Moore and Hasler, 2017). Nonetheless, the technology requires considerable expertise and the efficiency of embryo production is low (~25% of oocytes collected yield transferable embryos). Embryonic loss was greater for a frozen compared with a fresh embryo transfer indicating that current methods of freezing and thawing will damage the embryo (Crowe et al., 2025). Inconsistent responses among donor cows submitted to identical superovulation protocols continue to frustrate practitioners (Moore and Hasler, 2017).

Crowe et al. (2025) demonstrated that the embryonic losses through d 18 were identical for AI and fresh embryo transfer. Hansen (2020) raised an important question relative to embryo transfer in cattle. Specifically, if embryonic loss rates during the first week after breeding are ~30% then why doesn't the transfer of a high-quality embryo after d 7 (thus circumventing the embryonic loss before d 7) have a greater pregnancy rate when compared with AI? The observation that embryo transfer does not yield increased fertility relative to AI suggests that either the transcervical embryo transfer kills a percentage of embryos or an embryo that appears morphologically normal may not be viable when placed into the reproductive tract. There may be the need for additional training of embryo transfer technicians to reduce the observed embryonic loss. An equally important need is for improved methods of morphological evaluation of embryos before transfer that are predictive of subsequent fertility.

Oocytes collected from the ovaries of slaughtered cows and matured/fertilized in vitro can be used to produce transferable embryos for dairy producers. The use of slaughterhouse oocytes has the advantage of scalability (i.e., many oocytes can be collected, matured, and fertilized) and this could possibly reduce the cost of embryos. The disadvantage of slaughterhouse oocytes is the incomplete genetic information of donor cattle.

In vitro gametogenesis is an emerging technology where gametes are generated from pluripotent stem cells and live offspring are produced (Aizawa et al., 2025). Yoshino et al. (2021) demonstrated the viability of this technique in mice. By combining fetal ovarian somatic-cell like cells (derived from pluripotent stem cells) with pluripotent stem cell-derived primordial germ-cell like cells, the authors were able to construct cumulus oocyte complexes (termed rOvaroids) that could be used for IVF and generate live offspring. The importance of this or similar techniques is that cells could come from any tissue or blood of an individual animal, dedifferentiated into stem cells (i.e., induced pluripotent stem cells) and used to create a renewable in vitro supply of oocytes from the same animal. Stem cells derived from either female (Yoshino et al., 2021) or male (Murakami et al., 2023) individuals could be used in this process, thus enabling oocyte production from both elite cows and elite sires. Targeted DNA methylation editing of imprinting control regions using clustered regularly interspaced short palindromic repeats (CRISPR)-based technology could enable the production of elite offspring from sperm cells derived from 2 adult sires or oocytes derived from 2 adult cows (Wei et al., 2025). Scientific advances in laboratory animals and humans will inform the work being done in cattle (de Bruin et al., 2025).

Blastocyst-like structures derived from pluripotent stem cells are called blastoids. Blastoids are important models for studying developmental biology of humans because their cells are derived from a cell line and avoid the ethical concerns of using a human embryo in research (Cheng et al., 2025). Studies of blastoids in cattle are advancing rapidly and create the possibility of a large supply of transferable embryos from cell lines derived from an individual animal. The embryos would be genetically identical (clones) to the parent animal. Ming et al. (2025) combined bovine embryonic pluripotent stems cells (bEPSC), bovine extraembryonic endoderm stem cells (bXEN), and bovine trophoblast stem cells (bTSC) to efficiently create blastoids (Ming et al., 2025). Their work stopped short of demonstrating the viability of the blastoids when transferred into recipient cattle. Earlier work by the same laboratory demonstrated IFNT production from blastoids transferred into recipient cattle (Pinzón-Arteaga et al., 2023). This work awaits the demonstration of live-born calves from blastoids and subsequent demonstration of scalable production and freezing of blastoids for on-farm applications. Stem cells matured into viable oocytes or used to construct viable blastocysts hold promise for efficient embryo production in the future. This new technology could entirely change the bovine embryo transfer industry and revolutionize dairy cattle breeding.

In summary, the future of technology applied to reproductive management of dairy cattle will consist of the refinement of existing technologies that include estrus detection, timed AI, sperm sorting, genomics, and pregnancy testing (Table 1). There will also be emerging technologies that are "barely achievable" today but could become "routine" tomorrow. Some important questions are unanswered and await future research (Table 2). The collective result of new knowledge and new technology will drive further improvements in genetics, fertility, and efficient reproduction in high-producing dairy cattle.

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Notes

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Nonstandard abbreviations used: AI = artificial insemination; EBI = economic breeding index; IFNT = interferon tau; ISG = interferon stimulated genes; IVF = in vitro fertilization; NA = national average for EBI; PAG = pregnancy-associated glycoprotein.