Journal of Animal Science, 2021, Vol. 99, No. 2, 1–11

doi:10.1093/jas/skab038
Advance Access publication February 6, 2021
Received: 30 November 2020 and **Accepted:** 2 February 2021
Board Invited Review

BOARD INVITED REVIEW

Advancements in sensor technology and decision support intelligent tools to assist smart livestock farming

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Abstract

Remote monitoring, modern data collection through sensors, rapid data transfer, and vast data storage through the Internet of Things (**IoT**) have advanced precision livestock farming (**PLF**) in the last 20 yr. PLF is relevant to many fields of livestock production, including aerial- and satellite-based measurement of pasture's forage quantity and quality; body weight and composition and physiological assessments; on-animal devices to monitor location, activity, and behaviors in grazing and foraging environments; early detection of lameness and other diseases; milk yield and composition; reproductive measurements and calving diseases; and feed intake and greenhouse gas emissions, to name just a few. There are many possibilities to improve animal production through PLF, but the combination of PLF and computer modeling is necessary to facilitate on-farm applicability. Concept- or knowledge-driven (mechanistic) models are established on scientific knowledge, and they are based on the conceptualization of hypotheses about variable interrelationships. Artificial intelligence (**AI**), on the other hand, is a data-driven approach that can manipulate and represent the big data accumulated by sensors and IoT. Still, it cannot explicitly explain the underlying assumptions of the intrinsic relationships in the data core because it lacks the wisdom that confers understanding and principles. The lack of wisdom in AI is because everything revolves around numbers. The associations among the numbers are obtained through the "automatized" learning process of mathematical correlations and covariances, not through "human causation" and abstract conceptualization of physiological or production principles. AI starts with comparative analogies to establish concepts and provides memory for future comparisons. Then, the learning process evolves from seeking wisdom through the systematic use of reasoning. AI is a relatively novel concept in many science fields. It may well be "the missing link" to expedite the transition of the traditional maximizing output mentality to a more mindful purpose of optimizing production efficiency while alleviating resource allocation for production. The integration between concept- and data-driven modeling through parallel hybridization of mechanistic and AI models will yield a hybrid intelligent mechanistic model that, along with data collection through PLF, is paramount to transcend the current status of livestock production in achieving sustainability.

Key words: animal welfare, decision making, modeling, precision livestock farming, ruminant, sensor

Abbreviations

AI	artificial intelligence
DIKW	data–information–knowledge–wisdom
DL	deep learning
DMI	dry matter intake
DST	decision support tools
GPS	global positioning system
HIMM	hybrid intelligent mechanistic model
IoT	Internet of Things
ML	machine learning
PLF	precision livestock farming
RFID	radio frequency identification
RGB-D	red–green–blue and depth
SLI	structured light illumination

Introduction

For about 60 yr in the United States (circa 1940 to 2000), innumerable livestock experimental data were collected and analyzed (Tedeschi, 2019) mainly groupwise, reflecting the population's samples. Such approaches are still commonly adopted nowadays, though data are more often obtained on an individual animal basis and consistently, given the surge in the sensor technology initiated in the 2000s, as shown in Figure 1. In tandem with the development, evolution, and dissemination of the Internet of Things (**IoT**), sensor technology became available in many shapes, forms, and sizes. While the objective of sensors is clearly to collect data, the primary purpose of IoT is to facilitate the transfer of data through a network to be stored in the cloud, accessed remotely, and processed by cloud computing in powerful remote servers. The humongous amount of data collected (and stored) by the combination of IoT and sensors gave rise to the concept of big data, and, with it, scientists sought the modernization of agriculture (Tzounis et al., 2017). However, the rapid development and dissemination

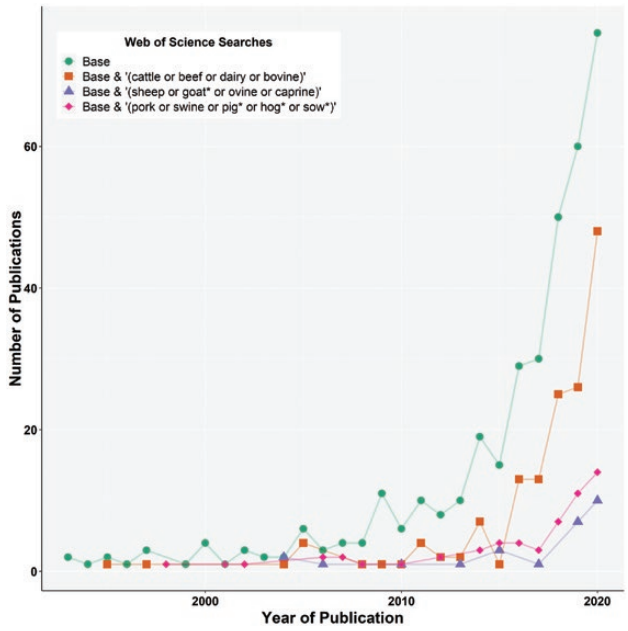

Figure 1. Progression of the number of publications reported by the Web of Science core collection database. The base search used the following criteria: "((precision near livestock near farming) or (smart near livestock near farming) or (smart near animal near agriculture) or (precision near animal) or (precision near livestock)) and (sensor* or automatic* or robotic* or electronic*)."

of IoT and sensor devices were not without drawbacks, at least for the end user. For example, sensor manufacturers may modify their devices to improve their performances, but updating a device may jeopardize compatibility with existing data. Thus, this creates a problem in the long run because it restrains the combination of data obtained from sensors of different brands or manufacturers for meta-analytical purposes and limits the use of the data for future applications, hindering their reliability and acceptability.

Amidst the evolution of sensors and IoT, researchers started to foment the concept of *precision* science based on the premise that it would sustainably increase food production and animal welfare. The agriculture community adopted the concept, and the term *precision agriculture* was coined as a means of optimizing productivity while preserving resources through the whole-farm management idea. The adoption of *precision agriculture* did not occur as quickly as anticipated because of the lack of proper decision support tools (**DST**) to apply it (Newman et al., 2000; McBratney et al., 2005). The DST is the software component of *precision* science that integrates data analytics with predictive analytics (i.e., modeling). The evolution in *precision animal* technology closely followed precision agriculture (Pham and Stack, 2018), though independent studies had already proposed individual animal management through DST to increase profitability and productivity (Tedeschi et al., 2004). It is not clear whether the failures in adopting DST by the animal science community and stakeholders were also related to the fact that additional information on individual animals (and their surroundings) was needed to customize the predictability of DST to be more precise and accurate.

In the animal science community, different terminologies, for example, precision livestock farming (**PLF**), smart livestock farming, and smart animal agriculture, to name a few, have been assigned to the same paradigm: how to sustainably increase food production while maintaining animal welfare and reducing environmental burden by merging data acquisition (sensors), storage (IoT), and transformation with prediction analytics using artificial intelligence (**AI**) tools (Tedeschi et al., 2017; Walter et al., 2017; Wolfert et al., 2017). These terminologies may have noticeable or subtle conceptual differences, but, in the end, they seek the same outcome of smartly or precisely managing livestock operations. Wathes et al. (2008) indicated that PLF uses principles and technology of process engineering to manage livestock production through "smart" sensors to monitor animal growth, milk and eggs production, endemic diseases, animal behavior, and components of the microenvironment within the production unit, such as temperature and gas emissions. Figure 2 illustrates the smart/precise and sustainable production paradigm by depicting the sensor technology. It shows examples that are currently available to gather data on diverse production scenarios for livestock. Advancements in sensor technology allow the capture of physiological, behavioral, and productivity measurements of individual animals to aid the smart/precise and sustainable production paradigm (Tedeschi et al., 2017; González et al., 2018), but, despite how data acquisition materializes for this paradigm, a common problem exists, the modeling component that may limit the applicability of the technology if not adequately integrated with the big data. The precision animal breeding concept deals with animals bred for a specific purpose, such as production use, environment, or market (Flint and Woolliams, 2008), and, although it is an essential component for successful animal production, it is not a cornerstone in the PLF concept despite ensuring livestock are well suited to the environment and elicit optimal responses to PLF.

Figure 2. Illustration of different sensor components associated with the IoT to assist in integrating DST within the concept of smart farming or PLF systems. Adapted with permission from Tedeschi (2020).

Halachmi et al. (2019) defined PLF as real-time monitoring technologies to manage the smallest manageable production unit, usually using a sensor-based individual animal approach or an animal-centric decision-making approach. Four critical considerations for smart livestock farming exist. First, wireless networks can handle the amount of data transmitted in "real-time" for herd management applications. For instance, for extensive systems, the wireless capabilities overcome most of the fixed location issues known in wired transmit. Second, wireless data transmit combined with AI are powerful enough to handle current PLF needs. Third, some PLF sensors are moving from devices worn by animals, where a sensor (e.g., collar activity monitor, leg pedometer, and rumen bolus) monitors a single animal, to sensors that monitor many animals concurrently. For example, a single camera captures data for many animals as they exit the milking parlor for lameness detection and body condition score (Spoliansky et al., 2016), or only one camera monitors the feed bunk to assess individual feed efficiency. Fourth, on-farm real-time analyses embedded in sensor devices or local farm computers are shifting to offline big data AI-based applications. However, because of the unique circumstances of extensive compared with intensive livestock systems, it is necessary to continue to evolve wearable devices that can provide data in a form suitable for real-time wireless transmission from remote sites within extensive systems for PLF applications.

Therefore, this review aims to highlight significant developments in data gathering using sensor technology and predictive analytics by applying modeling techniques to improve production, sustainability, and profitability of livestock operations, focusing on ruminant production around the globe.

Precision Livestock Farming

Grazing and foraging ruminants

PLF for ruminants in grazing and foraging systems presents unusual challenges, particularly for more extensive, remote properties with large land areas and livestock numbers. Extensive production systems for grazing and foraging ruminants require measurement technologies that have specific characteristics, including that they can: 1) be fixed on or worn by livestock; 2) be strategically positioned and used in locations on properties that have a higher frequency of visits by livestock such as watering and supplementary feeding points; or 3) provide broader-scale animal, pasture, and landscape measurement capacities, such as aerial or satellite imagery, and be used for wireless data processing and transmission on a spatiotemporal scale suitable for extensive livestock enterprises.

Technological developments for remote monitoring in extensive grazing systems have varied in their success and remain limited in uptake. In contrast, the use of sensing, imaging, and other measurement technologies within more intensive, confined systems has the advantage of enabling data transmission from within facilities where the livestock reside and are yarded and, for dairying, at least, are milked as in confined animals as discussed below. Similarly, within more intensive, smaller-scale grazing systems, it may be feasible to incorporate fixed measurement technologies such as imaging into grazing paddocks. Certain technologies can be integrated into facilities for livestock handling that are managed within more extensive systems. However, in these circumstances, the frequency of data collection, transmission, and sampling may be lower than desired. Hence, it may provide historical response data on livestock performance rather than real-time performance data, such as behavior and location within the grazing and foraging environment. In these situations, the historical response data can be used in time series analysis to access trends and provide means to forecasting performance.

Smart farming for extensive grazing and rangeland systems has the potential to include applications linking the environment, livestock, and the supply chain (Walmsley et al., 2014; Greenwood et al., 2016, 2018; Jorquera-Chavez et al., 2019), including metrics for climate, soils, herbage availability from pastures, and animal performance and products to enhance genetic improvement, management, and production optimization, predictions, and risk management. These applications, many of which are still being developed using AI, more specifically machine learning (**ML**), will enable

improvements in monitoring, objective measurement, and management of livestock, including their productivity, health and welfare, the landscape and environment, labor efficiency, and hence profitability and sustainability. The application of sensing, imaging, and other remote measurement technologies will enable further development of DST to enhance enterprise management. These tools require interfaces that producers can easily use, for example, BeefSpecs (Walmsley et al., 2014), and ideally can be linked to other enterprises across the supply chain. Examples of DST include genetic improvement programs, such as BREEDPLAN (https://breedplan.une.edu.au/), and precision management tools to enhance pasture, grazing, nutritional, and landscape management to improve reliability in meeting target-market specifications (McPhee et al., 2014, 2020; Walmsley et al., 2014). The capacity to link objective measurement tools, integrate data across the supply chain, and use the so-called dashboards that enable easy access to a range of DST will also support improvements in the extensive livestock industries (Greenwood et al., 2016, 2018).

Greenwood et al. (2016) reviewed the use and application of various sensors, imaging, and other emerging technologies concerning extensive beef production, and González et al. (2018) and Halachmi et al. (2019) further discussed the attributes of these technologies for livestock production in general. The range of remote, near real-time monitoring technologies being developed or applied or with potential applications for free-ranging livestock and extensive grazing and foraging environments is increasing rapidly and include 1) in-field fixed and ground-, aerial-, and satellite-based measurement of pastures, invasive weeds, and soil, water, and greenhouse gas monitoring using sensors, photogrammetry (Bloch et al., 2019), or other technologies including LiDAR (Fernández-Quintanilla et al., 2018; Reinermann et al., 2020; Segarra et al., 2020; Weiss et al., 2020); 2) multi-channel, satellite-based spectrometry (Segarra et al., 2020), such as WorldView-2 Satellite Sensor (https://www.satimagingcorp.com/satellite-sensors/worldview-2/), which may be coupled with weather and soil grids to model and predict pasture biomass components and to guide grazing management decisions for sheep and cattle (http://grazingapp.com.au/; Badgery et al., 2017); 3) body composition (McPhee et al., 2017; Miller et al., 2019; Zhao et al., 2020) and physiological assessments (Beiderman et al., 2014), including thermal imaging (Halachmi et al., 2008, 2013) to assess body temperature (González et al., 2013) using devices at, or fixed to, handling facilities; 4) automated in-field liveweight measurement (Nir et al., 2018) and drafting of livestock coupled with radio frequency identification (**RFID**) to determine individual or herd liveweight and growth of cattle (Charmley et al., 2006; González et al., 2014, 2018) and sheep (Brown et al., 2015; González-García et al., 2018a, 2018b); 5) virtual fencing using global positioning system (**GPS**)-enabled collars and a mobile phone app (https://www.agersens.com/) to remotely fence, move and monitor animals, and control herd or flock access to pastures and environmentally sensitive areas without the need for conventional fencing (Campbell et al., 2019, 2020); 6) on-animal devices to monitor location, activity, and behaviors in grazing and foraging environments (Dobos et al., 2014; González et al., 2014; Greenwood et al., 2014, 2017; Bailey et al., 2015b; Andriamandroso et al., 2016; McGavin et al., 2018; Rahman et al., 2018); and 7) early detection of lameness or other diseases (Van Hertem et al., 2014; Steensels et al., 2016). The RFID technology has also been used in conjunction with in-field walk-over-weighing units to enable researchers to identify parturition date (Aldridge et al., 2017; Menzies et al., 2018b), maternal parentage (Menzies et al., 2018a), postpartum estrus (Corbet et al., 2018), and welfare status more generally, and to draft animals for provision of supplementary nutrients and monitoring of the live weight and growth response (Imaz et al., 2019, 2020; Simanungkalit et al., 2020).

Classification of cattle behaviors that will underpin the development of a range of applications and DST in extensive environments has used "classical" ML algorithms (Handcock et al., 2009; Dutta et al., 2015; Smith et al., 2016), which are relatively simple to train. However, they require substantial engineering of features and have limitations in the number and types of behaviors that can be accurately classified and in the transportability of the behavior classifiers across devices and environments. Deep learning (**DL**)-based methods, such as sequential Deep Neural Networks, which can use raw sensor input data, have the potential to overcome these limitations and improve the accuracy and reliability of cattle behavior classifications (Rahman et al., 2016; Kumar et al., 2019; Peng et al., 2019). Further improvements that allow for on-device behavior classifications to enable wireless transmission of behavior data will also require methods that have low energy, computational, or memory needs to function on embedded systems within wearable devices.

The establishment of phenomics platforms for extensive livestock will also enhance DST development to improve livestock performance within extensive grazing and foraging environments. Livestock phenomics platforms can provide a broad and deep array of environmental and cattle performance and physiological data (Beiderman et al., 2014; Greenwood et al., 2016; Halachmi and Guarino, 2016; Spoliansky et al., 2016; Visser et al., 2020). In doing so, they may help to overcome current limitations in data collection and development of new (Bailey et al., 2015a; Pierce et al., 2020) and potentially more relevant productivity and efficiency traits, particularly for grazing cattle, that can be used in genomic and quantitative genetic selection and development of management tools and practices (Greenwood et al., 2016; Bailey et al., 2019). Such data capture and data management platforms will also enable the timely generation of environmental, health, and welfare metrics and practices to improve livestock well-being and environmental outcomes, which are increasingly being required for the provenance of livestock products available to consumers (Scollan et al., 2011).

Confined ruminants

Similar to grazing and forage ruminants, many PLF applications for confined animals exist. It started with electronic milk recording patenting in 1978, then real-time spectroscopy patenting in 2007 and 2011, to the more recent heat stress release patenting in 2021 (Halachmi, 2015; Halachmi et al., 2019), to list just a few applications. The main relatively new applications are monitoring individual feed efficiency, early detection of lameness, and early lactation diseases.

Monitoring individual feed efficiency

Feed cost represents as much as 65% to 75% of the operational expenses in intensive dairy or beef operations (the so-called confined ruminants); therefore, every few percentages of feed saved has a sizeable economic impact when encouraging the adoption of feed efficiency performance. There is a considerable variation between individuals, up to 30% (Halachmi et al., 2011, 2016; Ben Meir et al., 2018), and, consequently, phenotypic and genetic selection of individuals for their feed efficiency can have a substantial economic impact. Accordingly, PLF

applications for confined ruminants were developed, with the aim of improving feed efficiency. *Traditional* feed intake monitoring systems utilize individual weighing balances (electronic scales) and RFID antennas in feeding stalls to measure the amount of feed consumed by each animal. The electronic scale is the oldest (Halachmi et al., 1998) and likely the most straightforward sensor for measuring feed intake in group housing and feedlot settings. An electronic scale is placed in a feeding station and measures each feed's weight consumed by each animal during each meal at each feed bin. A manager can then decide how many electronic scales to deploy along a feeding lane given the number of animals. Several companies have developed electronic feed weighing systems, including the Calan Broadbent Feeding System, the Controlling and Recording Feed Intake system, the GrowSafe System, Intergado Efficiency, and the Roughage Intake Control system. Numerous researchers have evaluated these weighing systems (Halachmi et al., 1998; DeVries et al., 2003; Bach et al., 2004; Ferris et al., 2006; Wang et al., 2006; Chapinal et al., 2007; Stajnko et al., 2010; Mendes et al., 2011; Chizzotti et al., 2015), but, unfortunately, they have been infrequently used in commercial operations due to their high price and frequent cleaning and maintenance that many cannot afford (Wang et al., 2006; Stajnko et al., 2010). Furthermore, some of these systems also maintain full control over the collected data, and data manipulation is performed without a transparent process to the end user.

Recent research advancements have occurred with low-cost cameras and computer vision algorithms for designing individual feed intake measuring systems to overcome these obstacles. The camera is typically positioned above the ration pile or feeding lane. Several methods are used to represent a 3D geometrical position of the target surface visible to the camera.

Feed intake monitoring with structured light illumination

The structured light illumination (**SLI**) and time of flight (Lassen et al., 2018) methods refer to systems composed of a camera and light projector. The projector is used to project images of light patterns across the scene being monitored. An SLI system was applied for 3D scanning of dairy cow ration to determine the volume and weight of feed in a bin before and after feeding dairy cows (Shelley, 2013). When the SLI system was tested on 272 heaps in a laboratory, it showed a high variance between the calculated image weight and actual values (Shelley, 2013). Only 72% of the results were within 814 g of the difference between the estimated mass through image and the scale-measured mass. Unfortunately, the SLI requires controlled lighting conditions, tuning, and shading; thus, SLI systems currently work only in indoor conditions protected from sunlight.

Feed intake monitoring with calibrated stereo cameras

Multiple cameras in calibrated stereo configuration can be used to extract depth information on the objects via triangulation and analyze the disparity between corresponding points. Bloch et al. (2019) determined feed mass and volume using a photogrammetry method, which operates on several images of the object of interest (i.e., ration heaps) from various perspectives to create a 3D model of the object surface. The method was tested in laboratory and cowshed conditions, with 125 and 60 ration heaps, respectively. The estimated error for calculating the mass under laboratory conditions was 0.483 kg for ration heaps up to 7 kg. The SD for the cowshed experiment was 0.44 kg, resulting in a total error of 1.32 kg for ration heaps up to 40 kg in the cowshed (i.e., barn). A significant weakness of this approach is that the colored markers used for the point cloud processing would not be useful in a cowshed on a working farm because dirt can affect their colors, inadvertently detaching them from the floor and walls by the tractors that regularly operate in the barns. Additionally, eight cameras were required for a single heap, making this method impractical.

Feed intake monitoring with red–green–blue and depth cameras and infrared sensors

Red–green–blue and depth (**RGB-D**) cameras provide a combination of images representing RGB color wavelengths, along with the depth of objects. These cameras include a depth sensor based on an **IR** (infrared) or near-IR projector, and an RGB camera, resulting in in-depth information per pixel within the RGB image. The 3D data acquisition technique has been used in both research and industry to assess object surface conditions (Johnson, 2020). Several RGB-D feed intake methods and algorithms have also been developed for indoor (Shelley et al., 2016), outdoor, and open cowshed conditions (Lassen et al., 2018; Bezen et al., 2020). An RGB-D camera and DL algorithm were applied to overcome the effect of sunlight on the IR scanner (Bezen et al., 2020). The data tested were obtained in an open cowshed. The system directly measured the feed intake of a single meal, with a mean absolute error of 0.127 kg per meal; each meal was in the range of 0 to 8 kg. Currently, the method described by Bezen et al. (2020) looks promising. Perhaps, it will be improved when combined with eating behavior sensing (Halachmi et al., 2016). Empirical (i.e., statistical) modeling was used to predict daily dry matter intake (**DMI**) for many species (dairy cows, beef cattle, pigs, goats, and sheep; Seymour et al., 2019). These models were based on data collected using mechanical weighing systems (Halachmi et al., 2004, 2016; National Research Council, 2007; Volden, 2011; Holtenius et al., 2018). However, daily summaries of rumination and activity behavior sensors using "in-house" intensive systems are a poor indicator of DMI (Schirmann et al., 2012). Eating behavior (Halachmi et al., 2016), 3D camera (Bezen et al., 2020), or 2D photogrammetry (Bloch et al., 2019) may "deliver the goods." In 2020, Jiang et al. (2020) repeated the method developed by Van Hertem et al. (2018) and improved its accuracy to more than 98%.

Early detection of lameness

Lameness is second only to mastitis in terms of its detrimental effects on dairy herd productivity (Booth et al., 2004). The annual incidence of lameness ranges between 4 and 55 cases per 100 cows (Schlageter-Tello et al., 2014), depending on the farm, location, and year of study. The overall cost of lameness reported in the literature varies, from approximately US$ 446 per case in the United Kingdom (Esslemont and Kossaibati, 1997) to an average cost per case for a sole ulcer, digital dermatitis, and foot rot of US$ 216.07, US$ 132.96, and US$ 120.70, respectively, in the United States (Cha et al., 2010). Detection of severe lameness is relatively easy; however, by the time the animal becomes severely lame, successful treatment is less efficient. However, producers often miss subtle signs of lameness. A PLF monitoring system associated with a DST that could detect milder, subclinical lameness cases would be beneficial. Rajkondawar et al. (2002, 2006) hypothesized that measuring vertical ground reaction forces as animals walked over a force-plate system could provide the basis for early detection of lameness. The product StepMetrix was developed for lameness detection system by using a pressure-sensor mat on which cows walked once or twice a day (van der Tol et al., 2003; Chapinal et al., 2010; Van Nuffel et al., 2016), but these systems are relatively expensive. Van Hertem et al. (2011) developed a machine vision-based

system under Israeli conditions. Together with other animal-related data that already exist in the farm management software, parameters correlated with lameness were identified, including milk production and neck activity (Van Hertem et al., 2013b). A side-view concept (Van Hertem et al., 2013a) was replaced by a 3D camera placed above the cows (Viazzi et al., 2014). The combined 3D camera and animal production–behavior-related parameters appear to be the "winning setup."

Early detection of calving diseases

The PLF technology could be potentially efficacious in identifying calving diseases (such as mastitis and ketosis) affecting dairy cow mammary glands (Steensels et al., 2012, 2016, 2017a, 2017b). However, the end user (e.g., farmers and veterinaries) must also consider the usefulness of alerts for the systems. The relationship of false-positive and false-negative alerts almost always challenges biomarker effectiveness. The best designs will minimize both false positives and false negatives. Missed disease occurrences (i.e., false negatives) limit the system's value, with too many false positives potentially resulting in the livestock producer being forced to follow up on alerts that are not related to disease occurrence. Managing this balance is not always easy. In general, these challenges reflect the difference between the theoretical application of technologies and their practical and economic use in the field. This is a common problem in statistics mainly observed in "clinical trials" (Fawcett, 2006). While working on mastitis, Steensels et al. (2017a, 2017b) addressed a crucial issue on the transportability of an application. These authors showed that it is possible to create a model on one farm and validate it elsewhere as long as a local calibration procedure that allows automatic adaptation to local conditions is undertaken. This insight should be considered when a new PLF tool is being planned, developed, and validated.

Predictive Analytics

As discussed above, there are many possibilities to improve animal production through PLF, and the combination of PLF with computer modeling can facilitate its on-farm applicability. Contrary to the adoption experience observed with DST in the past (Newman et al., 2000; McBratney et al., 2005), producers appear to be adopting the PLF initiative and its modeling components at an increasing rate (John et al., 2016).

Currently, the majority of animal agriculture modeling is either empirical (Halachmi et al., 2001, 2004; Nitzan et al., 2006) or mechanistic (i.e., concept- or knowledge-driven; France and Kebreab, 2008; Tedeschi, 2019; Tedeschi and Fox, 2020). AI is a relatively novel concept in many science fields, including animal agriculture (Tedeschi, 2019), though its roots date back to the 1950s when the adaptive neural network algorithm was initially conceptualized (Widrow and Lehr, 1990). Two AI approaches are mostly employed these days. ML and DL are highly sophisticated, data-driven AI approaches based on neural network programming, though some ML and DL may include decision tree aspects in their algorithm. In this sense, ML has few layers of codes, usually less than five (this is a notional threshold that is not definitive), and each layer is based on neural network algorithms, whereas DL is a subset of ML algorithms that have multiple layers of codes, usually hundreds of layers or more, that can retro-feed themselves (i.e., backpropagated; Tedeschi, 2019).

Interestingly, for animal agriculture, AI-based approaches may be the *missing link* to expedite the transition of the traditional goal of maximizing output mentality to a more mindful purpose of optimizing production efficiency while alleviating resource allocation for production (Tedeschi and Menendez, 2020). AI, on the other hand, is a data-driven technology that can manipulate and represent the big data accumulated by sensors and IoT, though it cannot explicitly explain the underlying assumptions of the intrinsic relationships in the data core because it lacks the wisdom in the data–information–knowledge–wisdom (**DIKW**) hierarchy (Cannas et al., 2019; Tedeschi, 2019). Despite AI lacking the wisdom component, it provides a robust advancement in predictive analytics and provides the opportunity for the human element to reap wisdom.

The concept-driven (mechanistic) programming depicted in Figure 3A is provided in red (it also represents traditional [empirical] programming) vs. the data-driven programming (or learning, shown in blue) used by AI technology. In typical traditional (i.e., empirical) or concept-driven (mechanistic) programming, the algorithm (code) is hardcoded (software), and inputs (independent variables) are submitted to calculate the outputs (dependent variables), called model predictions (Figure 3A). With the boom in the development of expert systems in the 1980s, the *learning* era began to take shape, and the question became: can computers create a code given the inputs and outputs rather than making predictions based on inputs and codes? (Chollet and Allaire, 2018). For data-driven programming (learning paradigm), the algorithm (rules of the calculation logic) is generated based on inputs and outputs, as represented in blue in Figure 3A. That means AI approaches learn by comparing inputs and outputs to figure out the rules (codes) that can represent the data. The traditional (empirical) and concept-driven (mechanistic) approaches have dominated predictive analytics in many scientific areas, including animal science; the data-driven approach is still incipient but growing steadily (O'Grady and O'Hare, 2017; Tedeschi, 2019).

Each of these approaches has benefits and drawbacks that are, in part, intrinsic to their assumptions and computational

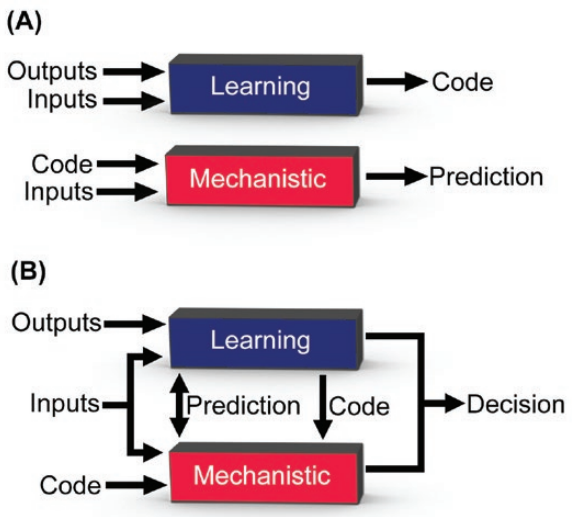

Figure 3. A graphical representation of how data-driven (learning, in blue) and concept-driven (mechanistic, in red) paradigms use inputs (independent variables), outputs (results), and codes (rules) for predictive analytic purposes (A). A theoretical representation of a parallel hybridization of data- and concept-driven paradigms (algorithms) in which *decision* represents a combined prediction that met the minimum acceptability threshold (B). Based on Cannas et al. (2019) and Tedeschi (2019).

barriers. For instance, the mechanistic approach, also referred to as deliberative thinking because it represents an abstraction of reality, is based on a vast scientific knowledge base. The principal benefit of this approach is that humans can analyze the results and learn from them, but the degree to which humans acquire new knowledge depends on the complexity, abstraction, and quality of the concepts used to build the mechanistic model in the first place. Perhaps the major limitation of mechanistic modeling is the time and effort required to make them and their intrinsic deterministic characteristics that might limit their applicability when uncertainty dominates the problem. The complexity of mechanistic modeling increases (possibly exponentially) as the modeling scope changes from a single, readily identifiable problem to issues that focus on systems with several integrated elements within a network. Given the complexity of animal production systems, it is nearly impossible to develop mechanistic models that could incorporate all perceived essential variables and their constraints and relationships in developing a concept-driven model. Thus, by design, uncertainty is inadvertently added to mechanistic models because of the simplification of reality. This means that fewer variables are deliberately included in the model to explain the impact of, otherwise created by, many variables. Therefore, innovative computational and modeling methods must be developed and used to ascertain the adequacy of mechanistic models because they are, in fact, a simplification of reality. Because of the inherited need to simplify problems to be modeled, there is a perception that reductionism leads to avoiding the incorporation of other fields of science in solving a problem. Reductionism and simplification are not necessarily the same thing. Reductionism tends to assume that the whole is the sum of the parts, whereas simplification seeks to identify essential elements that can mimic reality or the whole. Therefore, mechanistic models, which are, by default, based on the simplification of reality, can still be used in combination with other approaches to avoid extreme reductionism when solving complex problems.

Data-driven approaches, based mostly on AI technology, are not free of difficulties either. In addition to the lack of the wisdom component of the DIKW hierarchy (Cannas et al., 2019; Tedeschi, 2019), the data-crunching approach of AI-based technology is exceptional, but nothing is known about why a prediction is made (Knight, 2017). Furthermore, with the development of unsupervised learning (more recently referred to as self-supervised learning; LeCun et al., 2015), the search for predictive reasoning may become even more complicated, if not impossible. Another limitation of the data-driven approach is that its predictability is highly dependent on the quality of the training data and, of course, the independent variables (i.e., inputs) needed for future predictive purposes. AI is a powerful tool to use for large data sets, but AI predictions can be wrong. In fact, it has been shown that AI can fail miserably with simple tasks (Waldrop, 2019). Perhaps the failure in the predictability of AI is not the worst of its misdeeds. The fact that AI's predictions can be manipulated by adding ill-conditioned data into the database used to develop AI's predictive rules is more troublesome than its failure to predict correctly. The reason is simple; when ill-conditioned data are inserted into the database, the AI algorithm lacks the wisdom and proper instructions to identify the incorrect data. Once the data are inserted, AI cannot identify and certify the information used for development and validation purposes. This fact is more concerning than the inability to predict incorrectly because the predictability can have a high degree of certainty, even if it is a high degree of certainty of an incorrect prediction. Furthermore, it cannot discern an incorrect prediction or correct it by itself.

Assuming that ill-conditioned data are not used to develop or train AI models, the question then becomes: can significant advancements in predictive analytics be made if concept- and data-driven modeling approaches are integrated? (Tedeschi, 2019). Alternatively, would their intrinsic drawbacks be minimized or surpassed once the integration is achieved? While we do not have definitive answers to these questions, the integration has certainly been explored in different ways (Mertoguno, 2019). The integration of concept-driven (mechanistic) modeling with data-driven (e.g., neural network and AI) modeling, which requires big data, might substantially improve our ability to explain variability within acceptable boundaries and improve the model's predictability. For instance, Figure 3B shows a possible integration between concept- and data-driven modeling through parallel hybridization of mechanistic and learning programming paradigms, yielding a hybrid intelligent mechanistic model (**HIMM**). The HIMM may not enhance our ability to understand the underlying principles governing production systems or a problem, but they may well increase prediction precision and accuracy. Therefore, HIMM can become the heartbeat of the next generation of decision support intelligence tools, and when combined with the latest AI technology, such as natural language processing (https://www.gwern.net/GPT-3), unsupervised learning (i.e., self-supervised learning) will become one step closer.

In retrospect, scientists frequently have accursed the lack of data for our inability to make useful predictions or forecasts during the Animal Science discipline's establishment and development. Data became increasingly abundant as research stations were constructed around the world (Tedeschi, 2019), and, more recently, sensors and IoT became broadly available, alleviating challenges for the collection and storage of data. Through PLF, smart technology provided the opportunity for generalized DST adoption by livestock operations (O'Grady and O'Hare, 2017). Big data then became available, but scientists lacked the means to analyze until ML and DL became accessible. However, AI technology cannot achieve wisdom in the DIKW hierarchy because AI does not explicitly explain the underlying assumptions of the data and the particular combination of specific inputs to yield the outputs. The ebbs and flows in the evolutionary timeline in the Animal Science discipline reflect our incessant search for understanding the unknown to improve humankind (Cannas et al., 2019; Tedeschi, 2019). Despite our incomplete understanding of how AI works its way through the data to *learn*, it is a robust advancement in predictive analytics. The next generational wave in mathematical modeling may well be the hybridization between mechanistic and learning paradigms using, for example, HIMM. This, coupled with data collection through PLF, is paramount to achieving truly sustainable livestock production.

Acknowledgments

This article is based on presentations at the Production, Management, and Environment Symposium on Big Data, Artificial Intelligence, and Smart Farming Techniques during the 2020 Annual Meeting of the American Society of Animal Science, July 19 to 23, 2020, that was held online. We contributed equally to this manuscript, and the order of authorship is in alphabetical order, except for the corresponding author.

Conflict of interest statement

The authors declare no conflict of interest to disclose.

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