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Review article

Effects of the environment and animal behavior on nutrient requirements for gestating sows: Future improvements in precision feeding

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ABSTRACT

Taking into account individual variability while feeding a group of sows allows feed cost reductions and therefore improves animal efficiency. This precision feeding strategy is based on 1) nutritional models, which are able to predict daily individual nutrient requirements; 2) automatons, that can deliver individual rations; and 3) new technologies such as sensors which provide real-time information on the animal performance and life conditions that should be integrated into the estimation of requirements. Up to now, only production data (body weight, backfat thickness) have been integrated into the calculation of individual nutrient requirements.

However, the literature reported that health status and behavior, such as physical activity, social behavior, and location in the pen, can strongly influence nutrient requirements. A change in the feeding or drinking behavior can also indicate a health or welfare problem. Sensors, automatons and cameras are now able to detect some diseases or injuries, and record certain on-farm behaviors. Therefore, nutrient requirements should be adjusted based on these health and behavioral parameters. Environmental factors such as thermal conditions, housing type and noise level have also been reported to affect nutrient requirements. On-farm sensors can easily be installed to record these parameters to be integrated into the nutritional model and improve its precision. A decision support system can be used to integrate these new measurements into the nutritional model for gestating sows. It would also be helpful to trigger alerts and propose corrective actions when behavior changes or health issues are detected.

1. Introduction

Precision feeding is one way to better consider individual variability in feed and nutrient requirements within a herd (Gaillard et al., 2020a). It involves using technology to provide the right amount of feed, with the right composition and at the right time, to a

Abbreviations: AA, amino acid; CP, crude protein; SID, standardized ileal digestible; Lys, lysine; P, phosphorus; N, nitrogen; BW, body weight; BT, backfat thickness; LCT, low critical temperature; EAT, effective ambient temperature; UCT, upper critical temperature; THI, temperature-humidity index; DSS, decision support system; ML, machine learning.

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small group of animals or to individuals (Pomar et al., 2009). It aims to improve the sustainability of animal production by reducing farm costs and environmental loads, monitoring quality, and improving animal welfare. Applying precision feeding requires the assessment of the nutritional potential of feed ingredients as well as the nutrient requirements of each animal, to formulate balanced diets accurately and minimize nutrient deficiency or excess (Pomar et al., 2009).

Sow nutritional models have drastically progressed in recent years with a view to predicting daily individual nutrient requirements based on few inputs (Gaillard et al., 2019; Gauthier et al., 2019). Sensors and automatons have simultaneously been developed, thus allowing an automatic and real-time data collection, which leads to ration adjustments. To go further, behavioral, health, and environmental factors could also be taken into account by nutritional models to gain in precision and improve sow welfare by inducing alerts and actions when a negative health or behavioral event occurs. This review aimed to collect information on the effects of the welfare level (health and behavior, i.e., feeding and drinking behavior, activity, and social interactions) and environment (ambient temperature, humidity, light intensity, noise, and housing type) on sow feed requirements, in terms of quantity and composition, during gestation. It also assumes that the integration of this information into precision feeding systems to improve these systems will help improve animal welfare and create alerts for the farmer.

In the first section, we describe how the information available about health and body condition of sows, and their behavior, can contribute to improve the determination of their energy and nutrient requirements. In the second section, we review the information available about the effect of the environment, including climate, air quality, noise and type of housing. In the third section, we describe how the nutritional models available in the literature are able to handle all the criteria considered in the two previous section, in the daily requirement of individual sows in the perspective of precision feeding. The last section is more prospective and describes how new technologies such as the use a large diversity of sensors combined with machine learning could contribute to the development of on-line decision support systems (DSS) for improved efficiency, performance and welfare of gestating sows.

2. Behavior and health status are potential factors affecting nutrient requirements

This part of the review aimed to summarize the different behaviors, including physical activity, social interactions, feeding and drinking behaviors that are expected to affect nutrient requirements or to provide interesting information about health and welfare. Therefore, these behaviors are of interest in precision feeding. Nutrient requirements are indeed closely linked to the welfare of animals. Disturbances of the welfare state of animals include modifications of their general level of activity, social interactions and access to feed. Moreover, health issues that contribute to poor welfare often induce changes in these activities. Consequently, real-time recording of the behavior and health status of sows should help to build nutrient models that will better suit the current state of the animals, in addition to giving information about their welfare (Benjamin and Yik, 2019). The technologies associated with these measurements, their level of precision, advantages and drawbacks have been highlighted.

2.1. Feeding and drinking behaviors

2.1.1. Adequate feed supply

With the development of new technologies such as automatic feeders, individual and automatic recordings of daily feed intake and feeding behaviors are possible. A decrease in feed intake is known to be related to welfare-reducing health incidents. However, for gestating sows, which are usually fed restrictively, the consumption of their ration is often “all or nothing”. A sow that is able to stand up will visit the feeder and eat all of her ration in one visit (Gaillard et al., 2021), but where it is affected by a health issue, it will probably remain lying down in a corner of the room. Thus, feed intake might not represent the best indicator to anticipate the detection of health issues, but may help the farmer to identify which animal needs care. Recent work has shown that certain feeding behaviors are valuable indicators of illness or discomfort, and some can even be used to predict the risk of disease or injury (Weary et al., 2009). For example, sick calves reduced the number of non-nutritive visits (without milk intake) to the feeder, but not the number of nutritive visits (with milk intake), which highlights the fact that animals will reduce the frequency of sampling behaviors with the onset of illness (Weary et al., 2009). For growing pigs (barrows fed ad libitum meals), the time spent at the feeders increased until they reached 95–105 days of age, at which point it stabilized at 85 min per day (Brown-Brandl et al., 2013). In the same study, the gilts spent around 14 min less per day at the feeders than the barrows. References for sows in this area are rare, sow feeder data will thus need to be analyzed to determine whether nutritive or non-nutritive visits to the feeders as well as time spent at the feeders could be relevant indicators of health and welfare disorders. This would require the definition of a “baseline” number of non-feeding visits and time spent at the feeders to be able to detect variations due to an event or disease.

2.1.2. Adequate access to water

A lack of water supply has been linked with a decrease in feed intake, feed efficiency, and growth rate, which can lead to tail biting (Valros, 2018) and health problems. In practice, a decrease in water consumption can be used as an indicator of reduced feed consumption in weaned piglets (Dybkjaer et al., 2006), or as a predictor of diseases in lactating sows (Kruse et al., 2011; Zhu et al., 2017). For example, a decrease in water consumption can be observed in lactating sows approximately one day before physical signs of diarrhea are noted (Madsen and Kristensen, 2005). It is therefore interesting to measure and understand the drinking behavioral patterns of an animal over time (Kashiha et al., 2013; Andersen et al., 2014). Thanks to automatic water troughs equipped with water meters, the individual water consumption and number of visits can be recorded. However, precision is an important challenge while measuring water consumption, as some pigs play with water or just spill water on the floor while drinking, especially under hot conditions. Chen et al. (2020) developed a method based on video recording, which makes it possible to distinguish between drinking pigs and drinker-playing pigs. This method improves the accuracy of water consumption measurement as well as pig welfare estimation.

The water requirement for pigs is estimated to be around 10 % of their body weight (BW), so between 15 and 20 L per day per gestating sow, and between 20 and 35 L per day for lactating sows (Massabie, 2001). However, water intake varies with the feeding system, the type of diet and ambient temperature. Ad libitum water intakes are 20–25% higher than when water access is restricted, and may reveal a waste of water (playing behavior) or over-consumption in terms of physiological needs. In this last case, the excessive water intake, called polydipsia (Klopfenstein et al., 1996), is described as a compensation for feed restriction or poor housing conditions (Rushen, 1984). Water intake is highly fluctuating among sows, and between days for the same animal. Experiments under controlled temperature conditions have shown an inconsistent relation between ambient temperature and water consumption (NRC, 1981). Between 20 and 30 °C, the major increase in water consumption in growing pigs, when expressed as a function of dry matter intake, is primarily a function of the reduced dry matter intake with increasing temperatures above 25 °C (Fuller, 1965). Water needs at temperatures lower than 10 °C have not been reported yet. The two main nutritional factors known to increase water intake are the quantity of protein and mineral concentration, especially sodium and potassium (Massabie, 2001).

2.2. Body weight and backfat thickness

2.2.1. Body weight

As described previously, sow BW is a well-known measurement that has already been integrated into nutritional models. Body weight is highly variable between sows, and varies according to the stage of gestation (Young et al., 2005; Gaillard et al., 2019), being strongly related to the maintenance nutritional requirements. Body weight evolution is already an indicator of the health of the animal, as a sudden decrease often indicates a health disorder. Several new technologies are being developed to automatically record BW: foreleg weighing systems (Ramaekers et al., 1995), the walk-through weighing of pigs using machine vision (Wang et al., 2008) and photogrammetry to determine the three-dimensional shapes of pigs (Wu et al., 2004). Image analysis (Parsons et al., 2007) and analytic software are also being developed for the automatic and real-time estimation of individual BW via video recording (Kashiha et al., 2014; Pezzuolo et al., 2018). This would be a practical solution to collect daily individual BW on farms, by replacing scales, which are difficult to calibrate, and sometimes require staff to move the animals if the scale is not freely available in the group pen.

2.2.2. Backfat thickness

Similarly to BW, backfat thickness (BT) is a well-known measurement that has already been integrated into nutritional models to estimate nutrient requirements. It is measured manually using a small ultrasound scanner, so this procedure is time-consuming. Automatic measurement methods will need to be developed to gain time and precision, but are not available yet. Innovative technologies based on three-dimensional (3D) shape analysis are able to estimate the body condition of dairy cows (Le Colzer et al., 2019). This method could also be considered for sows and developed to automatize the image analysis once collected, and predict a score for sow body condition. In a study evaluating the welfare of gestating sows on 16 farms, Cariolet (1997) found an interesting relationship between the welfare of sows and their body condition. The frequency of body lesions, stereotypies and time spent standing after eating decreased when the body condition score increased. Conversely, excessively high BW and BT have been associated with locomotion and farrowing problems. Interestingly in this study, sow reproductive performances and welfare were positively correlated. An appropriate management of body condition and consequently of feed supplies therefore seems to be of major importance for sow welfare and performance.

2.3. Level of activity

In the gestating sow model described in Gaillard et al. (2019), activity is known as an important source of variability of energy requirements. Therefore, activity is included in the model but, until now, as a unique value for all sows based on an average daily standing time (240 min). It was calculated that the energy cost of standing in sows averaged 0.26 kJ.kg $BW^{-0.75}$. min^{-1} which is equivalent to doubling the instantaneous heat production during standing when compared to lying down (Noblet et al., 1993). Physical activity varies greatly between sows, farms, and housing systems (individual vs. group housing, indoor vs. outdoor housing). Indeed, multiparous sows seem to have a higher activity level (60 % more active) than first or second parity sows (Cariolet and Dantzer, 1984). In the same study, they found that the daily time spent standing varied much among the 4 farms studied, from 180 min per sow, up to 390 min per sow (mainly due to stereotypies). Feeding is also an activity that should be taken into account while calculating energy requirements, as it represents about 15 % of total daily heat production, including the heat increment of eating and the heat production due to the standing position (Noblet et al., 1993). Feeding time may depend on the type of diet, and especially its fiber content. Indeed, Ramonet et al. (1999) showed that sows fed a high-fiber diet spent more than twice as much time eating their daily ration (with the same energy supply) than sows fed a conventional diet, but conversely they spent more time lying down during the rest of the day. Overall, a shorter time standing was spent when sows received the high fiber diet (291 min. d) compared with the low fiber diet (363 min. d) with an intermediate value for the medium fiber diet (324 min. d).

Automatically recording individual on-farm activity would therefore serve as an input to better adjust feeding sow requirements. Recording activity levels require the use of sensors containing an accelerometer that can be fixed as an ear tag on the animal (Cornou and Lundbye-Christensen, 2012). These sensors usually measure the number of movements per hour for three different positions (lying down, standing, and walking). Sow activity in crates can also be automatically recorded using photocells (placed at a height of 0.6 m in the crate), and thin-film force sensors installed under the sows (Oliviero et al., 2008). The force sensor measures the overall movement of the sows, and the photocells are used to detect whether they are lying down or standing up. Software associated with video recordings is also being developed to estimate the real-time activity of each animal, based on motion and image analyses (Yang et al., 2020).

Activity levels are also sensitive indicators to help farmers to detect physiological events such as estrus (Labrecque et al., 2020), farrowing (Oliviero et al., 2008) or health disorders. The difficulty lies in the determination of the "baseline" activity level of each animal, with a view to detecting any perturbations.

2.4. Social behavior

2.4.1. Link between social behavior and feed requirements

The social behavior of pigs and their nutrient requirements are closely linked. Indeed, social tension may lead to an increase in aggressiveness, and thus loss of energy. When *ad libitum* access to feed is given, dominant sows spend more time eating, with longer and less frequent feeding bouts than low-ranking sows. Dominated sows move more: they were more often observed walking along the feed line. Sows with a low winning percentage during aggressive interactions gained less BW and BT during gestation than those with a high winning percentage (Norring et al., 2019). These sows were the ones with the lower relative BW. Feeding can also modify the aggression rate in groups of gilts and sows, and thus improve welfare. Indeed, for instance, the use of sugar beet pulp (500 g/kg) in the diet is associated with less aggression within the group than a control diet; in addition, it reduces the mean intake quantity compared to a control diet and increases the time spent eating (Danielsen and Vestergaard, 2001). The consequences of fibers on behavior depends a lot on the physicochemical properties of the fibers, soluble fibers having more impact than insoluble ones notably (Agyekum and Nyachoti, 2017).

2.4.2. Automatic detection of behaviors

The automatic detection of aggressive sequences in fattening pigs is possible through computer vision-based algorithms (Oczak et al., 2013; Viazzi et al., 2014; Chen et al., 2017). This method is even more accurate, as its initial step is to include only the aggressive pigs in the dataset (Chen et al., 2017), and not all moving pigs (Oczak et al., 2013; Viazzi et al., 2014). With this method (Chen et al., 2017), the mean accuracy (number of true positive and true negative recognition units / total number of recognition units) is 97 % for high aggression and 95.8 % for medium aggression (defined by Jensen and Yngvesson, 1998). Aggressive episodes are therefore very well recognized. Sensitivity (true positive recognition units) is 97.4 % and 90.6 %, respectively. This distinction between medium- and high-level aggression is promising for nutrition models based on energy loss. The use of information from stationary Kineth sensors fixed in the pig unit is also possible, with an accuracy of 95.7 %. Aggression is classified into head-to-head (or body) knocking and chasing with an accuracy of 90.2 %, with the use of two binary-classifier support vector machines in a hierarchical manner (Lee et al., 2016). This method is less costly but performances are slightly lower than for video-based methods. To our knowledge, no automatic system of visual detection of aggression in group-housed sows exists.

Aggressions, in addition to being characterized by a sudden increase in the level of activity, are associated with screams in sows (Tallet, personal communication), as is the case with fighting in piglets (Illmann et al., 2018) or in finishing pigs at the slaughterhouse (Briefer et al., 2019). Vocal parameters (e.g., duration of the screams, peak frequency, fundamental frequency, noise ratio) are specific to situations and emotions in encounters between animals (Briefer, 2012). Thus, having a tool that is able to automatically extract vocal parameters (Matthews et al., 2016; Mcloughlin et al., 2019), or at least the level of vocal noise in the group would be a useful tool for welfare evaluation. Such a system exists to detect the screams of piglets encountering pain (Schön et al., 2004). Extracting screams from background noise in growing pigs is automatically feasible thanks to the particularity of screams (formant structure, high frequency content, duration) (Vandermeulen et al., 2015) with a sensitivity of 72 % and a precision of 82 %. The difficulty would be to obtain individual data.

The integration of behavioral data in nutritional models would make it possible to obtain better precision for the calculation of the nutritional requirements of each animal while monitoring their welfare and health.

2.5. Location and proximity between sows

Location and spatial proximity may be an indication of thermal comfort in pigs, and may thus be related to feeding requirements (see section 3.1). High temperatures make pigs choose cooler places in their pen, and sometimes wallow in their own urine/feces (Pedersen, 2018), while cold temperatures make them lie down close together (Jackson et al., 2020), or even huddle in the case of young pigs (Huynh et al., 2005). Consequently, measuring location and spatial proximity may indirectly help to evaluate thermal comfort and thus adapt feeding strategies.

Methods to localize pigs exist, even if they have not been developed specifically for sows. For instance, the proportion of pigs in a certain area of the pen can be automatically determined using video image analysis (Nilsson et al., 2015). The area of interest is manually determined. Errors in the actual number of pigs in the area observed are estimated at 7.9 %. This method is promising, but still requires finding a way to identify individuals. Systems that aim at automatically detecting individuals are being developed in pigs (Alameer et al., 2020) with the use of cheap color cameras (Cowton et al., 2019). Pig locations are initially determined, then identities are generated and processed using multi-object tracking. This method thus allows the localization and tracking of individuals. The challenge is to keep track of an animal over a long period. For example, the identity of two animals close to each other could be confused by the identification system (Alameer et al., 2020).

2.6. Health status of the animal

The health status is closely linked to feed intake, either directly, as a poor health status may lead to a decrease in motivation to eat (e.g., inflammation associated with fever; respiratory problems), or may prevent the animal from moving (e.g., lameness); or indirectly, because food location is associated with a risk of tail biting and injuries (Valros, 2018).

Infrared skin temperature is a good indicator of the animal's reaction to cold/heat stress (e.g., sow: Ricci et al., 2019; piglet: da Fonseca et al., 2020). Individual temperature can be measured automatically using thermistors (that measure temperature with an electrical resistance) embedded in ear tags, or data loggers and infrared radiation sensors (that measure infrared emissions from the body) which make remote measures possible (Sellier et al., 2014; Benjamin and Yick, 2019). Also, ears, feet and snouts are the most sensitive body parts due to larger blood circulation; thus thermistors placed in ear tags are a good solution. Temperature is subjected to circadian rhythm and varies with the physiological status, i.e., gestation, digestion, feeding, and its measure therefore has to be carefully interpreted (Sellier et al., 2014).

Respiratory diseases can be automatically monitored via sound analyses. With this method, pathological coughing can be recognized, and distinguished from non-pathological coughing, background noise, and animal vocalizations (Berckmans, 2014). The method is based on a spectrogram analysis, and the use of algorithms or neural network processing. Recent studies show that this method can reach an accuracy of 96.8 % (Yin et al., 2020). Although technologically feasible, to date, continuous noise monitoring has not been integrated in animal welfare monitoring systems.

Lameness can be automatically detected by analyzing the gait, postural behavior and weight distribution of sows (Nalon et al., 2013). Lameness affects gait, as time spent standing is reduced, and activity, as walking distances decrease (Traulsen et al., 2016). Thus, ear sensors for position and acceleration monitoring have been used to distinguish between lame and non-lame periods for a single sow (Nalon et al., 2013). However, specific lameness detection is not appropriate, as activity may be affected by other factors, including other health issues. In addition, sows have an individual activity pattern that automatic systems need to take into account. Automatic video-based analyses can also be used to evaluate the walking gait (Nalon et al., 2013). Another method consists in putting

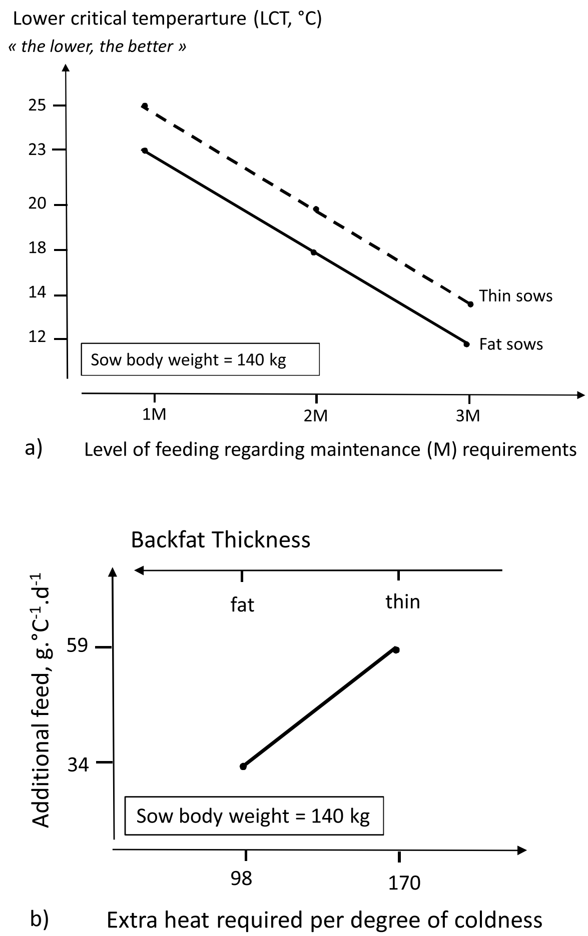

Fig. 1. Effects of feeding levels and backfat thickness (BT) on a) low critical temperature (LCT), and b) additional feed required per degree of coldness to compensate for extra heat loss.

the sow on a four quadrant scale to measure the weight it puts on each of its legs (Pluym et al., 2013). The weight put on a lame leg is lower than the weight put on a healthy leg, and lame sows can thus be detected. However, bilateral disorders are more complex to detect using this method.

3. Environmental factors are strongly linked with nutrient requirements

Choi et al. (2011) reported that factors such as average daily gain, stress, posture, and eating habits were all affected by environmental parameters (external temperature and humidity, housing conditions) and that their appropriate control could contribute to the improvement of precision farming and pig welfare.

3.1. Temperature

In conventional pig production, most sows are kept indoors, in climate-controlled buildings, and it is recommended to maintain the temperature within their thermal comfort zone, which is 16−20 °C on average (Verstegen and Curtis, 1988; Black et al., 1993). Sow heat-production rate mostly depends on their feed intake and metabolic BW, so under thermoneutral conditions temperature should not affect their heat-production rate (Blaxter, 1977) or nutrient requirements. Temperatures outside the thermal comfort zone may induce heat or cold stress with negative effects on sow health and welfare (Wegner et al., 2014a, b), but also on productivity (appetite, average daily gain, feed efficiency), which in turn affect nutrient requirements and may lead to nutrient deficiencies.

3.1.1. Cold stress

The low critical temperature (LCT) averages 16 °C for group-housed pregnant sows (Geuyen et al., 1984), and 20−23 °C for individually housed sows (Noblet et al., 1993), but varies with animal characteristics (i.e., sex, BW, activity, productivity), housing conditions and feeding (i.e., energy intake). Each animal eats different amounts of feed, and those with a relatively low feed-intake rate have a higher LCT, and are therefore especially vulnerable to cold stress. Holmes and Close (1977) combined different factors and estimated the LCT of group-housed sows of different BW (100 and 140 kg) and BT (thin or fat sows with the same BW) fed 1, 2 or 3 times what is needed for maintenance. The LCT was lower for heavier sows compared to lighter sows (22 vs. 25 °C, respectively, with sows fed at maintenance level). The LCT was lower for fat sows compared to thin sows (23 vs. 25 °C), and decreased with increasing feeding levels (from 23-18−12 °C respectively when fat sows were fed 1, 2 or 3 times the maintenance level, to 25-20−14 °C for thin sows; Fig. 1a). According to these values, for each extra 418 kJ ME consumed per $kg^{0.75}$/d, the LCT falls by 1 or 2 °C (NRC, 1981). Holmes and Close (1977) also calculated the extra feed needed to compensate for the increased rate of heat loss with the increasing degree of coldness, a term used to describe the magnitude of difference between the LCT and existing thermal conditions. A thin sow weighing 140 kg should consume additional feed (12 kJ ME/d) at the rate of 59 $g.d^{-1}$. $°C^{-1}$ of coldness, while a fat sow of the same BW should consume additional feed at the rate 34 $g.d^{-1}$. $°C^{-1}$ (Fig. 1b). These results underline the need to individually adjust feed allowances when the temperature is low.

3.1.2. Heat stress

The upper critical temperature (UCT) is defined as the effective ambient temperature (EAT) above which total heat production rate will rise and will be maximized (Holmes and Close, 1977). Rises in core temperature and in the frequency of respiration are also often observed (Heitman and Hughes, 1949). When considering heat stress, humidity must be taken into account as it participates in the increase of temperature (Morrison et al., 1967; Holmes and Close, 1977). Indeed, as an example, Holmes and Close (1977) reported that, at 30 °C, an increase of 18 % in relative humidity is equivalent to an increase in air temperature of 1 °C. Less information is available concerning the effects of heat stress on sow production traits, compared with cold stress. Based on data on short-term exposure to hot conditions (32 °C compared to 21 °C), barrows and gilts ate about 60–100 g less feed each day per °C of heat stress (Heitman and Hughes, 1949; Heitman et al., 1958). Heavier pigs are more sensitive to heat stress than lighter ones (Ingram, 1974). They are usually fatter and have a lower UCT. However, gestating sows are fed restrictively and heat stress should therefore rarely affect their feed intake.

3.1.3. Temperature humidity index

As indicated above, whether or not an animal experiences thermal stress not only depends on air temperature, but also on other factors such as the relative humidity. Indeed, lower temperatures may already induce heat stress in the case of high humidity. This has resulted in the continued development of climatic indices such as the temperature-humidity index (THI; Thom, 1959), used to define the level of heat stress. The THI has been used to define the level of heat stress in farm animals (Berman et al., 2016), including sows (Wegner et al., 2014b, 2016). According to the formula of the National Weather Service Central Region (NWSCR, 1976) the THI is calculated as follows:

$$THI = [(1.8 \times T) + 32] - [0.55 \times (RH/100)] \times [((1.8 \times T) + 32) - 58],$$

where T is the air temperature (°C) and RH the relative humidity (%). The THI thresholds for heat stress in sows have not been described in Europe (Wegner et al., 2014b). However, Wegner et al. (2016) used a threshold of 74 as a starting point based on heat stress for sows housed in closed insulated and ventilated barns in Germany, while the THI was calculated based on outdoor temperatures and humidity measurements. This THI index could easily be added to the model by calculating feed allowance and nutrient requirements for sows.

3.2. Housing

Since 2013, gestating sows in European countries have to be group-housed (EU Directive, 2008/120).

3.2.1. Type of floor

For growing and finishing pigs fed ad-libitum and raised on a well-insulated concrete floor, the LCT has been estimated at 13−14 °C and 10−11 °C, respectively. An increase in LCT of 3–4 °C has been reported when the pigs were housed on slatted floor (Verstegen and van der Hel, 1974; Mount, 1975). A wet floor increases the LCT even further (Mount, 1975; NRC, 1981; Fig. 2). Similar effects are expected on the LCT of gestating sows and should be verified, as a variation in LCT will affect feed requirements. Therefore, the type of floor and presence of bedding should be carefully considered.

Besides the insulating effect which decreases the LCT (i.e., decrease of 4 °C with straw bedding, Verstegen and Curtis, 1988), bedding allows the sows to exhibit their natural foraging behavior (Meunier-Salaün et al., 2001). In this case, the sows avoid spending extra energy for abnormal behavior such as bar biting and sham chewing (Cronin et al., 1986; Croney and Millman, 2007). Moreover, under cold conditions the straw eaten by the sows significantly contributes to thermoregulation (Noblet et al., 1989). Sows housed on concrete floors with wood shaving bedding had a higher activity (longer standing postures), less stereotypies and injuries (neck, head, side) than the sows housed without wood bedding (Zotti et al., 2019). These different studies suggests that bedding could have an effect on feed efficiency of gestating sows however it is difficult to estimate it as abnormal behaviors are decreased but standing and exploring behaviors are increased. The type of bedding, if any, must also be carefully chosen, and further investigation is required on that point.

3.2.2. Light intensity and duration

Based on an EU Directive (2008), a min of 40 lx during 8 h per day is required for pig farming in the EU. In Stevenson et al. (1983), when sows were exposed to 16 h of supplemental light during lactation compared to 1 h of supplemental light, litter weight at weaning increased and the post-weaning return to estrus was more synchronous. They also estimated that litter weight increased by 141 ± 6 g for each 10 lx increase in light intensity. This increase in litter weight was also reported by Mabry et al. (1982), who stated that the photoperiod may act directly on piglets to promote growth or increased suckling behavior. No relevant literature was found concerning the effect of light exposure on sow BW and feed intake. In dairy cow literature, feed intake increased, with a 16 h daily light exposure (Peters et al., 1981). In human literature, levels of light exposure influenced BW. In heavy pigs, an increased duration of the light exposure was also reported to modify pig behavior. Pigs that received 14 h–16 h of light per day spent more time resting and less time for other behaviors (pseudo-rooting, floor exploration, standing or sitting inactively) than pigs that received 8 h of light per day (Martelli et al., 2005, 2015). Based on these studies, rearing pigs in a semidarkness environment to avoid competition between the animals seems to be a baseless practice; while increasing the hours of light does not impair animal ability to rest and calmness level and improves growth parameters. The higher level of calmness with a longer duration of light exposure during the day may have reduced the amount of energy consumed and wasted for other behaviors. Light intensity and duration effects on feeding behavior, physical activity (standing and lying down), and exploration time should also be investigated in gestating sows.

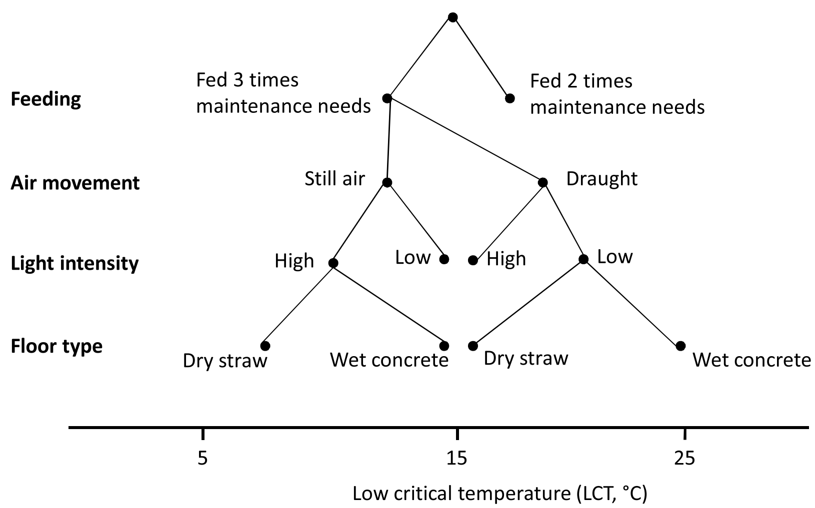

Fig. 2. Representation of nutritional and environmental effects on the low critical temperature (LCT) of group-housed pigs of 60 kg (from Close, 1981).

3.2.3. Noise level

Noise disturbs animals, and induces behavioral (Bowles, 1995) and physiological changes such as an increase in stress hormone (Turner et al., 2005). Based on an EU Directive (2008), a 85 dB threshold is required for pig farming in the EU, and should not be exceeded for long periods of time; sudden noises should also be avoided. In practice, noise levels vary with barn equipment and management (room cleaning, air system, feeding system, number of animals per room). For example, manual feeding systems are noisier than automatic ones. Dry feeding systems are less noisy than wet feeding or fully automatic liquid feeding systems, with or without sensors. Measuring and comparing the noise level of automatic feeders for precision feeding with one of the dry feeding systems would be relevant. When doing so, it is important to consider that with the use of an automatic feeder for precision feeding, sows are calmer and quieter when the farmers are nearby, as the latter are no longer associated with feed distribution. It would be useful to measure the noise levels before, during and after feeding over a longer period of time to reveal the specific effects of feeding on noise levels. Furthermore, the number of feeders per sow, and consequently the possibility for all the sows to receive feed at the same time, or over a given period, should also be taken into account when comparing the noise levels of different feeding systems. The floor type and ventilation system also contribute to the noise level. For instance, the noise level was lower when the animals were housed with straw bedding than on fully or partially slatted concrete floors (Wegner et al., 2019).

Several studies reported the negative effects of the noise level on pig productivity. Pigs exposed to 90 dB prolonged or intermittent noise showed a decreased growth rate (Otten et al., 2004). At 100 dB–135 dB minor effects were observed on the rate of feed utilization, weight gain, feed intake, and reproduction rates of boars and sows (Dufour, 1980; Manci et al., 1988). Noise levels also affect pig behavior: at a prolonged or intermittent noise of 90 dB, time spent lying down increased and social interactions decreased (Otten et al., 2004). According to Talling et al. (1996) pigs show an aversion to sudden loud noises, even more so when the noises are combined with high frequency and intensity (i.e., 500 Hz and 97 dB), although habituation occurred relatively quickly (Kittawornrat and Zimmerman, 2011). In 2009, Fottrell reported that noise levels above 85 dB must be avoided in buildings where pigs are kept, which is part of the EU Directive (2008). In the study of Algers et al. (1978), with sudden noise exposure pigs immediately started to search for the origin of the sound and continued for the whole 10 min period of the noise. Some trials showed that pigs respond with an increased activity when exposed to a short-term noise stress (Talling et al., 1996, 1998; Kanitz et al., 2005). Effects on activity and social behavior will affect feed and nutrient requirements. Therefore, short-term noises and noise levels in general should be monitored continuously and integrated into nutritional models.

The use of acoustic signals might also be an interesting approach for controlling and improving precision feeding devices. Ernst et al. (2005) showed that fattening pigs were able to learn that they had access to feed only after an individual acoustic signal was given. Kirchner et al. (2012) used this approach to develop a gestation feeding station with the individual calling of group-housed sows using a tri-syllabic name for each sow. They showed that this method was efficient to reduce agonistic interactions and body lesions.

3.3. Gases

Noxious gases such as ammonia (NH_3) and carbon dioxide (CO_2) can affect animal health and productivity in several direct and indirect ways (Choi et al., 2011). In Europe, the only regulations concern the level and duration of exposure of employees, but there are no animal-related regulations regarding a gas exposure threshold. The duration of the exposure, concentration levels and simultaneous presence of other aerial pollutants or environmental factors can cause significant harm. The behavior of the animal during acute or chronic (exposed for several days or months) exposure to NH_3 reflects how the animal reacts to noxious gas. No literature has been found on gestating sows concerning this topic, but few effects have been reported on growing pigs. Massabie et al. (1997) reported that high levels of gases (NH_3, CO_2) could decrease appetite and average daily BW gain at temperatures from 17 °C to 28 °C for growing-finishing pigs. At 24 and 28 °C, increasing air velocity to renew the air and avoid increasing gas concentrations increased the growth rate and feed consumption, but decreased feed efficiency, due to higher fat deposition. Pigs housed at 24 °C with still air were less active than pigs housed at a cooler environmental temperature (20 °C), or with increased air movement. At an ambient temperature of 20 °C with high air velocity, 90 % of the pigs began to huddle together. Therefore, air quality should be controlled continuously to optimize the need for a ventilation system and guarantee the health and productivity of the pigs. Such information could also be integrated into sow nutritional models, following further investigation and experimentation in gestating sows.

To briefly summarize this part, many environmental factors appear to affect feed intake and nutrient requirements. They are easily observable and recorded manually or with the use of simple sensors (temperature, humidity, and gas emissions…) on farms, and could therefore be added to nutritional models. However, more experiments are required on gestating sows to determine optimum environmental and housing conditions, and the consequences on nutrient requirements if variations occur.

4. Current nutritional models and decision support systems for sows

4.1. Nutritional models

Since the eighties, different mechanistic models describing the energy and nutrient utilization of the gestating sows have been published in the literature (Williams et al., 1985; Dourmad, 1987; Whittemore and Morgan, 1990; Pomar et al., 1991; Pettigrew et al., 1992; NRC, 1998; Dourmad et al., 2008; NRC, 2012; Hansen et al., 2014; Gaillard et al., 2019). Most of these models share the same concepts. They simulate energy and nutrient partitioning among the different functions and represent the sow as the sum of multiple compartments: body protein, body lipids, body minerals and the uterus. Equations describing nutrient utilization by sows calculate daily nutrient and energy flows from feed to storage in the maternal body and conceptus, and then excretion. They simulate the daily utilization of key nutrient pools by a sow and also predict the energy, amino acid (AA) and mineral requirements of sows based on production objectives, as well as changes in body composition resulting from a given feeding strategy or housing conditions (Fig. 3). The most recent sow model was published by Gaillard et al. (2019). It is based on a combination of current knowledge of nutrient use of gestating sows with the flow of data produced on-farm. This model considers individual variability in daily nutrient requirement according to gestation stage, sow characteristics at mating (age, parity, and body condition), and expected reproductive performance (number and weight of piglet at farrowing). This is new paradigm of models, “data ready” and “precision feeding ready”, and able to process both historical farm data (e.g., post assessment of nutrient requirements) and real-time data (e.g., to control precision feeding).

4.2. Feeding strategies of gestating sows

4.2.1. Phase feeding strategies

Dourmad et al. (2015) used InraPorc to evaluate two-phase and multiphase feeding strategies during gestation. Simulations indicated that, compared to one-phase feeding strategies, the two-phase and multiphase strategies respectively reduced crude protein (CP) intake by 10 % and 14 %, standardized ileal digestible (SID) lysine (Lys) intake by 11 % and 17 %, phosphorus (P) intake by 5% and 7 %, nitrogen (N) excretion by 15 % and 20 %, and P excretion by 9% and 12 %, and feed costs by 8% for multiphase (Fig. 4).

4.2.2. Simulation of precision feeding

Dourmad et al. (2017) developed a decision support tool for the precision feeding of gestating sows based on InraPorc (Fig. 3). The optimal supply for a given sow is determined each day based on a factorial approach that considers all the information available concerning the sows (genotype, parity, gestation stage, etc.). The energy supply was calculated for each sow to reach a target BW and BT at farrowing (Gaillard et al., 2019). Precision feeding with the daily and individual mixing of two feeds with different lysine concentration was then simulated and compared to conventional feeding (fixed mixing of two feeds with an average lysine concentration). Compared to conventional feeding, simulations indicated that precision feeding reduced total SID Lys supply by 27–32% depending on the farm (Fig. 4), and reduced the number of under- or over-fed sows (Gaillard et al., 2020b). Adapting the feeding strategy during gestation to capture changes in nutrient requirements more adequately seems to be a promising approach for reducing N and P excretion whilst decreasing feed costs. Indeed, continual nutrient adjustment should have an economic advantage because it can be based on a mixture of two feeds, a more expensive one to satisfy higher requirements, and a less expensive one to satisfy lower requirements.

4.2.3. On-farm

The “on-farm” application of precision feeding to gestating sows requires the design and development of measuring devices (for feed intake and sow BW), calculation methods and a feeding system that provides the required amount of feed with a composition that optimizes animal performance while minimizing the use of farm resources (Pomar et al., 2009). This approach is becoming possible in particular with the development of automatic feeders, sensors, and models that help elaborate an actual DSS. A recent experiment on gestating sows reported that with precision feeding the amount of lysine ingested decreased by 26 % compared to a conventional feeding strategy (fixed mixing of two diets with low and high nutrient concentrations; Gaillard et al., 2021).

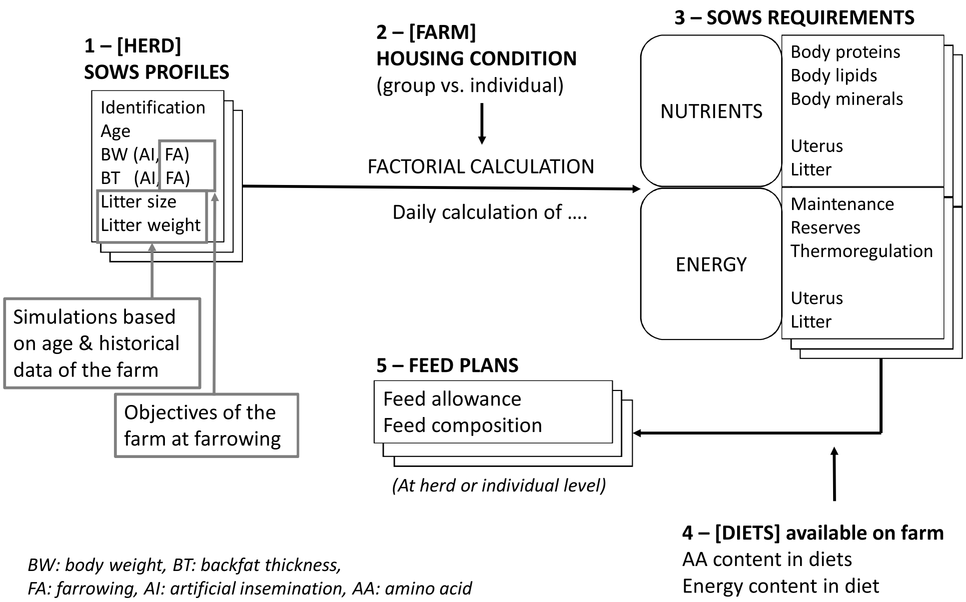

Fig. 3. Gestating sow nutritional model.

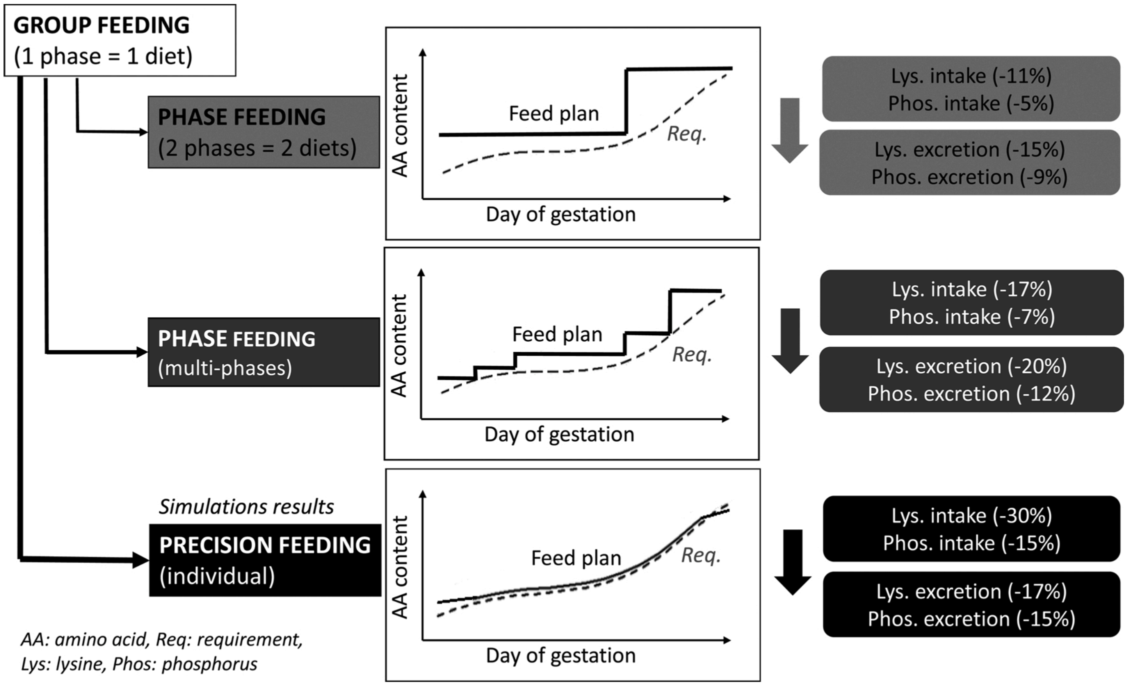

Fig. 4. Effects of feeding strategies on lysine and phosphorus intake, nitrogen and phosphorus excretion, for gestating sows (data from Dourmad et al., 2015 and Gaillard et al., 2020a).

4.3. Uncertainties and model adjustments

4.3.1. Quality of data produced

Sensors provide large amounts of data on a daily basis that need to be cleaned up and sorted to extract the signal of interest from each measurement. For this extraction, the data are usually smoothed with a level based on the objective (Friggens and Robert, 2016). These data then serve as inputs to models to predict animal nutrient requirements, and therefore need to follow detailed cleaning rules and thresholds to be repeatable and trustable. Furthermore, precision is also required in practice when delivering the feed. Recent experiments revealed that sow feeders which can mix two diets for precision feeding showed limitations, as the feeders had to deliver a proportion of feed of at least 50 g to guarantee adequate precision, while, sometimes, the calculated requirements for one of the two diets to be mixed were lower (Gaillard et al., 2021).

4.3.2. BW estimation

In the model proposed by Gaillard et al. (2019) to predict average sow energy requirements throughout gestation, the calculation of the maternal BW objective at farrowing was only performed once, at insemination, based on the age of the sow and according to a mean growth curve adjusted to the farm. To better deal with inter-individual variability, it would thus be interesting to consider the actual evolution of the sow BW, and when possible of the sow BT (only one measurement at insemination is currently included in the model), to adapt the energy supply during gestation. This implies the development of a system that makes it possible for the DSS to collect data on the evolution of sow BW and BT, and the progressive adaptation of each sow to its specific situation. This can be achieved by using automated weighing scales, whereas the measurement of BT is still performed manually. New analytic software is being developed for the automatic and real-time estimation of individual BW via video recording (Kashiha et al., 2014; Pezzuolo et al., 2018). This would be a practical solution to collect daily individual BW on farms, with possible additional information on body condition, by replacing the scales and their regular calibration uncertainties. As shown in dairy cows, 3-D image analyses might also be of interest to evaluate the body condition of sows (Le Cozler et al., 2019), but the technology has not yet been evaluated in sows.

4.3.3. Adjustment of nutrient supplies

In Gaillard et al. (2020b, 2021) precision feeding was achieved by mixing two diets whose formulation was primarily adapted to improve AA supplies. Although mineral concentration was also different between the two diets, precision feeding was less efficient for improving the adequacy between P supplies and requirements, because the dynamics of the evolution of requirements between P and AA are different. In the future, it might be interesting to formulate the diets based on AA and mineral requirements simultaneously and therefore mix three diets. Jondreville and Dourmad (2005) used a factorial approach to estimate digestible P requirements for maintenance and production in different physiological stages. Based on this approach and the more recent reviews of NRC (2012) and Bikker and Blok (2017), the estimation of P and calcium requirements was recently adapted for gestating sows and included in the nutritional model presented in Gaillard et al. (2019). This approach considers the influence of the type of diet (pellets or mash) and the addition of phytase for P digestibility. The model makes it possible to adjust dietary P supplies to sow and litter performance. However, P requirements for growth are estimated based on animal BW or protein gain, which has certain limitations. More mechanistic models have recently been developed, in which mineral concentrations (P and calcium) can vary independently of protein and lipid mass (Letourneau-Montminy et al., 2015), but until now they had been developed for growing pigs only. Such deterministic and mechanistic research models can be used to improve decision support tools and develop feeding strategies that minimize P excretion, while also considering the changes in calcium requirements.

Besides the above adjustments needed, these nutritional models used for precision feeding could also gain in precision by taking into account behavioral and health measurements if any relation with feed intake or energy and nutrient requirements is established. Indeed, new technologies have been developed in recent years, thus allowing high throughput measurements of individual sow behaviors.

5. Automatic systems to adjust feed and nutrient supplies, and reduce welfare problems

As described earlier, certain environmental, behavioral and health measurements could be integrated into the nutritional models to adjust feed intake or nutrient supplies individually and in real time. This supplemental information in the DSS also aims to improve welfare and health by inducing alerts based on changes in behavior and performance, partly solved by automatized actions.

5.1. Machine learning for animal behavior studies

Recent advances in sensors have revolutionized the acquisition of complex real-time data sets on behavioral and health information (Table 1). However, extracting knowledge such as individual behavioral or social interactions is still a daunting task. From a data science point of view, and especially for machine learning (ML), the challenge lies in proposing algorithms i) to characterize recorded behaviors (normal/abnormal) based on heterogeneous data acquired on different time scales, and ii) to understand the interactions between animals, especially if they are subject to disturbing events (climate variation, noise, toys, human presence or variation in feed allowance). Machine learning aims at providing a description or a model of the underlying behavior of the system observed by the data. The main purpose of this model is to be used in a prediction task for each new data entry.

5.1.1. Supervised and unsupervised techniques

The ML algorithms are usually classified between supervised learning techniques and unsupervised learning ones. The majority of high-performance and practical methods use supervised learning methods that rely on labelled data (samples) to train the model. Both approaches require a sufficient amount of data for this function. If data volume is not problematic in the context of animal monitoring (multiple sensors recording all day long), the availability of a sufficient number of samples may be questioned when considering supervised learning techniques. Labelled data actually results from a human data annotation task of videos, images, and audio datasets. This is an expensive task which requires qualified staff in animal welfare.

Table 1
Data recorded using different sensors and their application to nutrition, welfare and health in pigs (Cornou and Kristensen, 2013; Matthews et al., 2016).

Data recorded	Sensors	Application to nutrition, welfare and health
Identification	RFID ear tag Facial recognition	Individualization of data collection for other sensors
Body Weight	Automatic weighing 2D and 3D image analyses Pressure exerted by the front legs	Feeding precision Growth prediction Real-time welfare and health monitoring
Body temperature	Thermic camera Ear tag Bolus (internal sensors) Imaging analysis of thermoregulatory behavior	Parturition disorder monitoring Real-time health disorder monitoring Complementary of farmer observations
Water consumption	Water meter Image analysis	Detection of intestinal and behavioral disorders
Feed intake	Electronic Feeding system	Feeding precision Consumption prediction Performance monitoring Feeding behavior study Group monitoring of sow health problems
Physical activity	Accelerometer Radio waves Tracking using camera GPS sensors	Feeding precision Consumption prediction Detection of the beginning of parturition Posture and locomotion
Social behavior	Camera 2D and 3D image analyses	Real time welfare and health monitoring Social hierarchy study Detection of tail biting
Sounds: vocalization, coughing, scratching	Microphones	Real-time monitoring of respiratory and other diseases

Few studies have yet focused on unsupervised methods. Most of these methods use classical ML techniques such as clustering. The main objective of clustering is to find groups of elements that share the same properties. However, having groups of animals that behave in the same way does not provide much information about the behavior itself. Wang (2019) proposed to go further by training a hidden Markov model to describe the animal behavior model based on GPS data. The movement states delivered by the hidden Markov model are interpreted based on the annotation of movement paths, which means the approach is still dependent on human expertise. The method of Gauthier (2021) proposes to train a behavior prototype for the feed intake of lactating sows. The clustering is performed on a timed series to extract the prototypes that account for the behavior of the group (the feed intake trajectory), and allow online forecasting to calculate dietary requirements using a nutritional model.

5.1.2. *Learning from animal behavior*

Learning from animal behavior is less straightforward than from highway driving actions, for instance, for which artificial intelligence has allowed great breakthroughs. Supervised methods seem to be the more appropriate approach to achieving realistic and reliable results. The goal is not only to infer the global animal behavior model but also to be able to use it in a real-time behavioral monitoring system to improve welfare (Fig. 5). In this seminal work, Matthews et al. (2016) developed an automated monitoring system for tracking pig movement using a depth video camera. This study validated predictions of standing, feeding, and drinking behaviors without requiring a threshold method. More recently, Vázquez -Diosdado et al. (2019) have dealt with "concept-drift" occurring in the classification of dynamic elements. In the case of animal behavior classification, this means that the current behavior class of an animal will not necessarily be its future behavior class. Consequently, the on-line adaptation of the behavior model should be performed to improve the reliability of the animal monitoring system. The method that combines supervised and unsupervised methods (KNN and k-means) has been experimented on three sheep behaviors (walking, standing, lying down).

Cornou and Kristensen (2013) showed that monitoring systems in pig production can prevent and detect earlier health disorders using body temperature, BW, water consumption, feed intake and coughing. For example, the monitoring system described by and Lundbye-Christensen (2008) uses feeding behavior for detecting lameness and health disorders in group-housed sows. Monitoring the drinking behavior of growing pigs can help monitor intestinal disorders (Madsen and Kristensen, 2005; Kashiha et al., 2013).

5.1.3. *Interpretability of the models*

A promising approach would be to train a behavior model at an individual level for monitoring animal welfare. This monitoring system should be able to give aggregated and human-understandable information about the behavior of an animal, individually and within the group, for the analysis of its social interactions. As for any monitoring system, the system should be able to highlight abnormal situations. One crucial point involves the interpretability of models that allow decision-makers to understand recommendations in the short term, and to have full confidence in their decision-making tool in the long term. The focus will therefore be on the interpretability of the algorithms developed, so that the information extracted from the data may be used as a decision-making tool both by breeders for specific decisions (e.g., caring for animals), and by different breeding devices and equipment for real-time actions (e.g., modification of feeding, or the breeding environment).

5.2. *Proposed actions to solve welfare and health problems*

When monitoring automatic systems identify behavioral anomalies, real-time recommendations should be provided to improve welfare or health. These recommendations may involve various actions related to feeding, heating, enrichment materials or lighting.

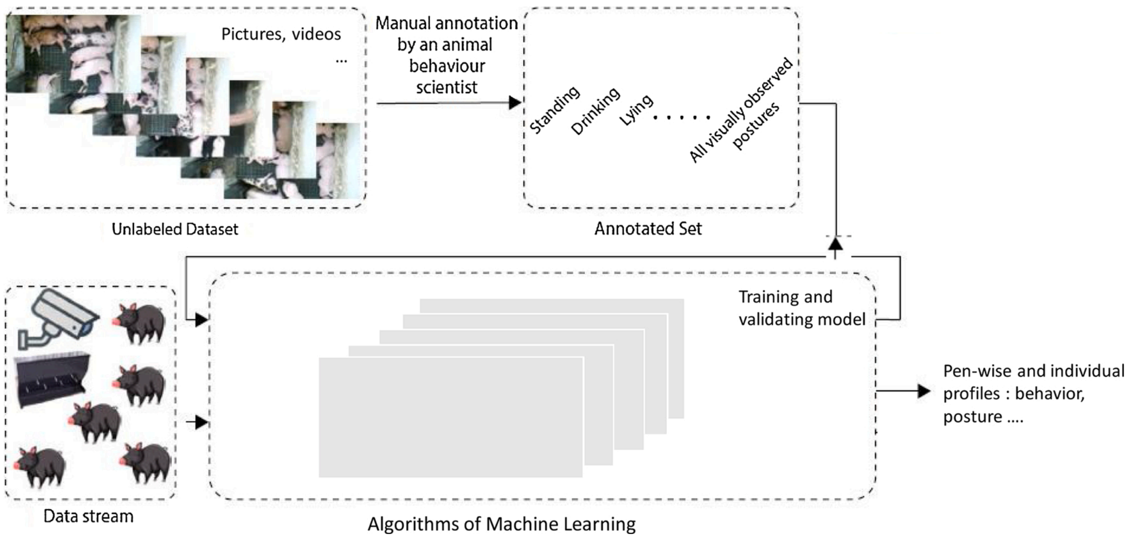

Fig. 5. Automated recognition of pig behaviors using deep learning (inspired from Alameer et al., 2020).

Only potential automatic solutions are listed below.

One possible corrective action involves the modification of feed composition (i.e., more fibers) or the individual level of feed allowance. Thanks to automatic feeders, feed requirements can be achieved with a variable mixture of two diets that make it possible to adjust the ration to the physiological state or according to sow activity regularly and individually (Gaillard et al., 2020b). For example, knowing that a standing sow needs twice as much energy as a sow that is lying down (Noblet et al., 1993), when an increase in activity is detected, feed allowance could be automatically increased and the diet composition modified accordingly. Philippe et al. (2008) showed the positive effect of the addition of fibers in the ration of gestating sows on their welfare. Fiber-enriched diets are also interesting to induce satiety while avoiding excessive energy intake (Meunier-Salaün and Bolhuis, 2015). This leads to a reduction in the occurrence of abnormal behaviors such as stereotypies, frequent in gestating sows. Nowadays, the EU Directive (2008) indicates that sows should receive a sufficient amount of voluminous or fiber-enriched feeds as well as feeds with a high energetic content to satisfy their hunger and need for chewing. The automatic supply of fibers in the ration, or sows spreading out in the room to play, could therefore constitute solutions to a detected welfare problem.

The automatic emission of positive sounds for sows can represent a corrective action to decrease aggressive behaviors. Pigs use their vocalizations to recognize and communicate with their pen-mates. They can express positive or negative emotions with a huge range of vocalizations and grunts (frequency, duration, amplitude) in response to the situation (Marchant et al., 2001; Friel et al., 2019). Emotional contagion based on behaviors can occur between piglets in a single pen (Reimert et al., 2017). Therefore, broadcasting "positive" vocalizations during a fighting period detected by real-time video analysis, or an increase in activity measured using accelerometers, could be tested with the aim of reducing or ending such events in a group of sows. Another similar solution to reduce agonistic behaviors could be to adjust lighting duration or its intensity.

In the case of cold thermal stress being detected, the automatic activation of warming lamps or heaters to increase the ambient temperature inside the barn might be a solution to reduce cold stress impact on sow productivity and welfare. Conversely, fans, sprinklers or cooling methods can be triggered in the case of detected heat-stress events (McGlone et al., 1988; Eichen et al., 2008). As shown previously, heat or cold thermal stress can impact the welfare and health of the sow. Reducing this stress can immediately help avoid this kind of problem by maintaining the climate within the thermal comfort zone for gestating sows.

The automatic emission of "pleasant" smells can also be considered to improve the welfare of gilts and sows. In pigs, olfactory communication is important in relation to social and sexual behavior, but also sow-piglet recognition (Marchant et al., 2001). Some molecules such as the 5a-androst-16-en-3-one natural pheromone can decrease agonistic behavior in growing pigs (Petherick and Blackshaw, 1987). However, this olfactory solution has yet to be tested and evaluated before it can be used on a commercial farm.

6. Conclusion

New feeding strategies are taking into account individual variability and trying to feed each animal closer to its requirements. Therefore, precision feeding aims at feeding an animal with the right ration (allowance and composition) at the right time. The nutritional models used to calculate feed allowance and nutrient requirements could gain in precision by taking into account certain environmental and individual behavioral measurements which have been reported to affect feed intake or nutrient requirements. Thanks to the development of new technologies, these data can easily be collected on farms with the use of sensors or video recording and analysis. However, more experiments are still needed on sows to quantify the effects of sow environment and behavior on nutrient requirements.

This review also makes the assumption that the integration of such information in precision feeding systems will not only improve productive parameters, but also establish a system of alerts and actions that aim to improve animal welfare. This decision tool should be flexible and understandable to maintain user trust in automatic systems, and scalable enough to provide efficient support. This approach is aimed at a new generation of breeding systems that is able to collect more information automatically (behavior, feeding, and activity…) with a view to improving the welfare and health of sows without decreasing their productivity or increasing feed costs.

It presents relevant interests for all stakeholders in the field. Breeders are primarily concerned, with the increasing number of animals per farm, as it is more difficult for them to follow each animal. An automatized system that is able to detect problems sufficiently early would help breeders to save time and decrease their stress on that point. The DSS system can be seen as the farmers' third eye but not as their substitute. Society is also more and more concerned about animal welfare and health. Such a system can meet societal demand by providing evidence of good rearing conditions for sows and gilts. Certain certifications and other market specifications could use the data of the DSS to evaluate the farm as part of a quality insurance scheme, for example by counting the number of alerts emitted over a given period. Finally, the livestock equipment sector could also benefit from this new approach by combining modeling and data mining with decision-making. These new technologies can make it possible to develop more precise and effective new sensors and robots. IT start-ups and companies are also starting to work in the field of agriculture. They provide a fresh approach to breeding equipment, which can help to improve the development of this field.

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Declaration of Competing Interest

The authors report no declarations of interest.

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