Conclusion and implications
Overall, the model predicted DMI and milk components well, but milk volume was overpredicted by any of the 3 schemes used in the model.

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4. Predictions of body mineral content in gilts from mating to first parturition: evaluation of different requirement models

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Introduction
The estimation of calcium (Ca) and phosphorus (P) requirements is generally based on a factorial approach. Regarding replacement gilts requirement models, they are based on equations obtained in growing pigs that have been extrapolated to larger animal which may affect the accuracy of estimates. However, data of body composition of gilts are scarce. With the objective of precising P and Ca requirements of replacement gilts, data of body composition of gilts from mating to first parturition have been generated and compared with existing prediction equations.

Material and methods
Body composition of 24 Swiss Large White gilts from the Agroscope sow herd was measured by dual-photon X-ray absorptiometry (DXA, i-DXA, GE Medical Systems, Glattbrugg, Switzerland) at mating, 40- and 80-days post-mating and day 2 after parturition. Back fat thickness was measured at P2 position at mating and on day 2 after parturition. Empty body weight (EBW) and body Ca and P were calculated according to Kasper et al. (2021) from DXA total weight, lean, and bone mineral contents outputs. Gilts were fed restrictively (2.36 ± 0.20 kg/d) a gestation diet (per kg, 12.1 MJ digestible energy; 2.7 g digestible P; 7.9 g Ca). The body composition models for growing pigs of NRC (2012), INRAE (Jondreville and Dourmad (2005)), Agroscope (Ruiz-Ascacibar et al. (2019)), CVB (Bikker and Blok (2017)), and of Dourmad et al. (2021) for sows were used to evaluate their ability to predict body P and Ca content of gilts. Evaluation was based on errors

Table 1
Comparison of observed and predicted body phosphorus and calcium contents.

Models	N	Driving force	Mean (g/gilt) Obs.	Mean (g/gilt) Pred.	RMSPE %[1]	ECT %[2]	ER %[2]	ED %[2]
Phosphorus								
INRAE (2005)	81	BW[3]	1025.1	873.1	15.7	89.2	5.3	5.5
Ruiz et al. (2019)	81	EBW[4]	1025.1	939.5	9.5	77.4	7.3	15.2
Bikker and Blok (2017)	81	EBW	1025.1	955.1	8.0	72.7	4.4	22.9
Dourmad et al. (2021)	39	EBW,P2[5]	995.1	1022.9	6.2	20.7	6.6	72.7
NRC (2012)	81	Protein	1025.1	864.3	16.4	91.9	0.8	7.3
Dourmad et al. (2021)	81	Protein	1025.1	945.7	9.2	70.6	9.2	20.2
Calcium								
Ruiz et al. (2019)	81	EBW	1748.3	1443.5	19.0	84.3	7.6	8.1
Bikker and Blok (2017)	81	EBW	1748.3	1516.7	15.0	78.4	7.0	14.6
Dourmad et al. (2021)	39	EBW,P2	1684.3	1655.1	8.9	3.7	16.2	80.0
Dourmad et al. (2021)	81	Protein	1748.3	1529.9	14.9	70.6	10.5	18.9

[1] RMSPE(%): RMSE expressed as percentage of the observed mean value.
[2] ECT(%), [2]ER(%), [2]ED(%): expressed as percentage of mean square prediction error.
[3] BW: Body weight (kg).
[4] EBW: Empty body weight (kg).
[5] P2: Back fat thickness (mm).

between predicted and observed values and mean square prediction error (MSPE) that was decomposed into error of central tendency (ECT), error due to regression (ER), and error due to disturbances (ED).

Results and discussion

Most models showed a high root MSPE (RMSPE) due to the high error of the ECT showing an underestimation of both P and Ca (Table 1). The equations for sows of Dourmad et al. (2021) based on EBW and P2 showed the best accuracy of prediction, with about 6 and 9% of error respectively, and mostly (>70%) related to disturbance. The results are contrary to the conclusion of these authors indicating that body protein content was the best predictor of body Ca and P. This discrepancy may come from the fact that the newly acquired body composition data in modern gilts, and especially body protein that is required to estimate P content, appears to be overestimated (RMSPE%: 9.54; data not shown) when using Dourmad et al. (1997) equation as proposed in Dourmad et al. (2021).

Conclusion

Results of this work showed that gilt EBW is the best predictor of body Ca and P growth from mating to first parturition.

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5. Future directions: An overview of data-driven and mechanistic modelling approaches of performance and sustainability in poultry

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Application

Mechanistic models (**MMs**) have provided vital decision-support, opportunity analysis, and performance optimization capabilities to poultry production systems for decades. The role of MMs has been questioned, partially due to the emergence and use of data-driven (**DD**) or machine-learning (**ML**) modelling approaches, with strengths in forecasting and prediction. This review will examine the historic and current use of MMs and ML in the poultry sector and hypothesize on future avenues for the application and hybridization of approaches in the "big data" era.

Introduction

As the global population is predicted to increase to 9.5 billion in 2050 (FAOSTAT, 2022), the need to efficiently produce food, particularly animal protein, will only continue to increase. Moreover, livestock industries are taxed with minimizing the impact of animal agriculture on the environment (e.g, methane, nitrogen, phosphorous, water & land use), while managing increasing societal pressures to reduce production intensity (e.g., pasture-based systems, slow-growing breeds) and remove antibiotics and hormones from feed. These pressures may impair efforts to improve efficiency and production. Such processes are difficult to optimize within individual production facilities, individual research trials, or qualitatively extract from scientific literature. Models can distill wisdom from scientific knowledge and identify optimized feeding and mitigation strategies when dealing with complex systems (Ackoff, 1989; Tedeschi, 2019). Mechanistic models define how a biological system works based on mathematical descriptions of biological principles. As such, they are commonly used to explore causality and provide a platform for examining new mode-of-action hypotheses in research (e.g., Ellis et al., 2011, 2012) and teaching tools to help students grasp interconnected biological processes (Gous, 2014). In practice, MMs have served as decision-support and opportunity analysis tools within animal production systems for decades.

Methods

This review explores the historical and current use of MMs in poultry production systems, their utility for the future, and how they may interact with new digital tools and technologies. In parallel, we will examine the emergence of ML and big data in the poultry production sector, as we universally strive for precision feeding and automation of animal production systems.