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Early-life growth performance and litter characteristics predict gilt selection and first mating success under commercial conditions

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Highlights

- Early-life growth performance predicts progression to transition and first mating under commercial conditions.
- Maternal origin explains a substantial proportion of variability in gilt growth traits.
- Larger litters are associated with reduced birth weight but not with weight at 220 days.
- Gilts from more homogeneous litters show higher selection and progression rates.
- Predictive modelling identifies birth weight and early ADG as key determinants of gilt development.

Abstract

Background: Efficient gilt replacement is critical for productivity and sustainability in commercial swine systems. Early-life growth and litter characteristics may influence the likelihood of females progressing through key developmental stages; however, their combined predictive value under commercial conditions remains insufficiently characterised. This study evaluated whether early growth performance and litter-level traits predict progression to the transition phase and attainment of first mating using conventional and machine learning approaches.

Methods: A total of 510 female piglets from 77 litters sired by eight boars of the same genetic line were monitored from birth to approximately 220 days of age under commercial farm conditions. Recorded variables included birth weight, transition weight (40–46 days), body weight at ~220 days, and average daily gain (ADG) across growth intervals. Litter characteristics comprised total born, number born alive, number born dead, female proportion, and selection ratio. Variance components attributable to sire and dam were estimated using linear mixed-effects models. Progression to transition (n = 346/520) and attainment of first mating (n = 346 monitored) were analysed using logistic regression and Random Forest models with stratified 10-fold cross-validation.

Results: Birth weight was positively correlated with transition weight ($r = 0.51$, $p < 0.01$) and early ADG ($r = 0.34$, $p < 0.01$), but showed weaker associations with body weight at 220 days ($r = 0.17$, $p < 0.01$). Litter size negatively affected birth weight ($r = –0.29$, $p < 0.01$) but was not associated with weight at 220 days. Maternal effects accounted for 39.9% of birth weight variance, declining to 10.5% at 220 days, whereas paternal variance remained below 3% across traits ($h^2 = 0.006–0.13$). Logistic regression identified birth weight as the strongest predictor of transition (OR = 1.66 per additional

kg). Random Forest models demonstrated moderate discriminative ability for transition (AUC = 0.77) and first mating (AUC = 0.74), with early ADG emerging as the most influential predictor of first mating attainment.

Conclusions: Early-life growth performance, particularly birth weight and pre-transition ADG, significantly influences gilt developmental progression under commercial conditions. Maternal and litter-level effects explain a substantial proportion of early growth variability. The integration of machine learning approaches improves individual-level prediction beyond traditional regression models and supports data-driven gilt selection strategies aimed at enhancing reproductive efficiency and herd sustainability.

Keywords: gilt development; early growth; litter effects; replacement efficiency; predictive modelling; commercial pig production

Backgroud

Gilt replacement constitutes one of the most significant recurring investments in commercial pig production systems, representing approximately 35–45% of annual sow herd maintenance costs (1, 2). These costs arise not only from rearing and housing expenses but also from non-productive days, delayed puberty, and premature culling of females that fail to reach breeding targets (3, 4). Consequently, improving the biological and managerial efficiency of gilt selection is critical to enhance herd longevity, reproductive performance, and overall production sustainability.

The economic burden of gilt replacement has been widely recognized as a significant contributor to overall production costs in commercial swine systems. Economic modeling studies indicate that high gilt replacement rates increase the number of parities required to achieve a positive net return(5). This is due to the substantial investment associated with gilt rearing and the lost productivity that results from removing gilts prematurely. Sector-level analyses corroborate these findings, estimating that the direct cost of raising a replacement gilt—including breeding, feeding, and management—can approximate several hundred euros per animal, with only a fraction recouped if the gilt is culled at a later stage (6).

The capacity of a replacement gilt to reach first mating at an optimal age and body weight is largely determined by developmental processes established during prenatal and early postnatal life. Increasing evidence supports the concept of developmental programming in swine, whereby intrauterine environment and early growth influence ovarian development, endocrine regulation, metabolic competence, and subsequent reproductive lifespan (7, 8). Early postnatal growth has also been associated with markers of ovarian reserve and reproductive potential in prepubertal gilts (9, 10). Thus, early-life growth performance may serve as a practical proxy indicator of later reproductive potential under commercial conditions (4).

Birth weight has been consistently associated with postnatal growth, age at puberty, fertility, and sow longevity. Low-birth-weight females generally exhibit reduced average daily gain, delayed sexual maturation, and lower lifetime productivity compared with heavier littermates (1, 11, 12). However, birth weight alone does not fully explain variation in gilt performance. Litter-level characteristics—including total litter size, number born alive, within-litter weight variation, and sex ratio—may reflect uterine capacity, placental efficiency, and early maternal support, all of which can influence both individual growth trajectories and the proportion of females meeting replacement criteria (13, 14). Additionally, females originating from male-biased litters may be exposed to increased prenatal androgen concentrations, potentially affecting subsequent reproductive performance (15-17).

Despite this growing body of evidence, relatively few longitudinal studies have simultaneously evaluated individual growth traits and litter-level determinants of gilt progression under standard commercial management. Most previous research has focused on experimental or selected populations, often including extremely low-birth-weight piglets that would not typically enter commercial replacement pools (8, 12). Consequently, there remains limited information describing how early growth dynamics and litter composition interact to influence practical selection decisions, such as progression to the transition phase and attainment of first mating, in large-scale production systems.

Integrating longitudinal growth data with multivariable analytical approaches may improve the identification of females with higher developmental potential. Predictive modelling techniques, combined with conventional statistical analyses, may help disentangle the relative contributions of birth weight, postnatal growth rate, and litter characteristics to gilt progression under commercial conditions.

Based on these considerations, we hypothesised that (1) superior early-life growth performance increases the probability of progressing through key developmental stages, including transition and first mating; and (2) litter-level factors exert an independent influence on gilt selection outcomes beyond individual birth weight. Therefore, the objective of this study was to evaluate whether early growth traits and litter characteristics predict progression to the transition phase and attainment of first mating under commercial farm conditions, using both conventional statistical analyses and predictive modelling approaches.

Methods

Animals and management conditions

The study was conducted in collaboration with two commercial pig farms located in the Region of Murcia, Spain: Casa Sabas and Fontana, both belonging to CEFU S.A.

A total of 510 female piglets born between 4 and 10 February 2020 were initially selected from 77 litters sired by eight boars of the same genetic line (Landrace × Large White). Gilts and sows were managed under standard commercial conditions.

Farrowing occurred in individual crates with partially slatted flooring. Piglets were weaned at approximately 28 days of age and transferred to nursery facilities with fully slated floors and automatic feeding systems. Animals had ad libitum access to water and were fed age-appropriate commercial diets formulated according to industry standards.

Health management followed the routine vaccination and veterinary protocols established by the company, including vaccination against major endemic pathogens according to regional guidelines.

Ethical statement

All procedures were conducted in accordance with European Directive 2010/63/EU and were part of routine farm management. The protocol was reviewed and approved by the Animal Ethics Committee of the University of Murcia (project code 34071).

Selection criteria at birth

At farrowing, all piglets were individually identified and weighed using a calibrated digital scale (±10 g). Female piglets were included in the study if they met the following criteria:

- Birth weight > 1.0 kg
- Absence of visible congenital abnormalities
- Normal vitality and suckling behaviour within 12 h postpartum

For each litter, the following data were recorded: farrowing date, dam and sire identification, total born (TB), number born alive (NBA), number born dead (NBD), sex distribution, number of selected females, and individual birth weight.

Two litter-level indices were calculated:

- Female proportion (%) = (number of females born / TB) × 100
- Selected female proportion (%) = (number of selected females / number of females born) × 100

Transfers and measurements

After lactation period, 344 gilts were transferred to the rearing facility and weighed upon arrival (transition weight).

At approximately 220 days of age (219–225 days), body weight was recorded again. Gilts were considered to have reached first mating when they were inseminated following detection of standing estrus under standard farm reproductive management protocols. Animals with missing identification or incomplete records were excluded from subsequent analyses.

Growth performance

Average daily gain (ADG, g/day) was calculated from individual weight records for three growth intervals:

- Birth to 40–46 days of age
- Birth to 219–225 days of age
- 40–46 days to 219–225 days of age

ADG was calculated per piglet using:

$$\text{ADG} = \frac{W_{\text{end}} - W_{\text{start}}}{\text{Days between measurements}}$$

where $W_{\text{end}}$and $W_{\text{start}}$are the weights at the end and start of the interval, respectively.

Statistical analysis

All statistical analyses were performed using IBM SPSS Statistics 28.0 (IBM Corp., Armonk, NY, USA). Data are expressed as mean ± standard error of the mean (SEM) or as percentages, as appropriate.

Differences in categorical variables (e.g., proportion of selected females) were assessed using Chi-square or Fisher's exact tests. Continuous variables (e.g., birth weight, body weight at 220 days, ADG) were analysed by one-way ANOVA or Kruskal–Wallis tests when data were not normally distributed. Correlations were calculated using Pearson's coefficient (r). Statistical significance was set at $p < 0.05$.

Mixed-Effects Modelling of dams and sires

To properly account for the hierarchical structure of the data (piglets nested within dams and dams nested within sires), growth traits were analyzed using linear mixed-effects models.

For each dependent variable (birth weight, transition weight, body weight at 220 days, and average daily gain), a model including only an intercept as fixed effect and random intercepts for sire and dam (nested within sire) was fitted:

$$Y_{ijk} = \mu + Sire_j + Dam_{k(j)} + e_{ijk}$$

where:

- Y_{ijk}represents the growth trait of the ith piglet,
- $Sire_j$is the random effect of the jth sire,
- $Dam_{k(j)}$is the random effect of the kth dam nested within sire,
- $e_{ijk}$is the residual error.

Variance components were estimated using Restricted Maximum Likelihood (REML). The covariance structure for random effects was specified as variance components (VC).

The proportional contribution of each variance component was calculated as:

$$\frac{\sigma^2_{component}}{\sigma^2_{total}}$$

where total variance was defined as the sum of sire, dam, and residual variances. Narrow-sense heritability (h^2) was approximated from the paternal component as:

$$h^2 = \frac{4\sigma^2_{sire}}{\sigma^2_{total}}$$

Pseudo-R^2 values were computed to describe the conditional variance explained by the full model.

Predictive modeling of transition phase

Transition status (1 = reached the transition phase; 0 = did not) was the dependent variable. Features included: birth weight, total number of piglets born (TB), number born alive (NBA), number born dead (NBD), female ratio, and selection ratio.

The dataset was analyzed using Orange Data Mining v3.9. Logistic regression and Random Forest algorithms were compared. Models were evaluated using 10-fold cross-validation, and performance metrics included area under the ROC curve (AUC), classification accuracy (CA), precision, and specificity. Logistic regression coefficients (β) and odds ratios (OR = e^β) quantified the effect of each predictor. Variable importance in the Random Forest model was assessed using the mean decrease in Gini index.

Predictive Modeling of first mating phase.

Data was collected from 346 gilts from birth until their potential first mating phase. The binary target variable indicated insemination status (1 = yes; 0 = no). Eleven predictors were included: birth weight, litter size traits (TB, NBA, NBD), female selection ratio, transition weight (day 46), body weight at 220 days, and ADG across phases.

Logistic regression and Random Forest algorithms were applied using Orange Data Mining v3.9 with stratified 10-fold cross-validation. Performance metrics were identical to those in 2.6.1: AUC, classification accuracy, precision, and specificity.

Results

Body weight at birth, during transition, and at 220 days of age and average daily gain (ADG) across growth phases

Descriptive statistics for body weight at birth, at the transition period (40–46 days of age), and at approximately 220 days of age are presented in Table 1. The reduction in sample size across stages reflects selection, culling, mortality, and incomplete longitudinal records.

Table 1. Descriptive body weight statistics of female piglets at birth, transition, and 220 days (Mean ± SEM, kg).

Parameter	N	Minimum	Maximum	Mean	SEM
Birth weight (kg)	510	1.00	2.28	1.39	0.01
Transition weight at 40–46 days (kg)	342	4.47	12.10	7.38	0.07
Weight at 220 days (kg)	309	100.0	198.5	152.49	0.98

Average daily gain (ADG) was calculated for three growth intervals: birth–transition, transition–rearing, and birth–rearing (Table 2).

Table 2. Average daily gain (ADG, g/day) during growth intervals.

Growth interval	N	Mean (g/day)	SEM
Birth to 40–46 days of age	342	138.34	1.56
Birth to 219–225 days of age	297	811.37	5.44
40–46 days to 219–225 days of age	297	680.90	4.52

All correlations between body weight and ADG at different stages were positive and statistically significant (Table 3). Birth weight was strongly correlated with both transition weight (r = 0.51, p < 0.01) and ADG during transition (r = 0.34, p < 0.01), but its relationship with weight and ADG at 220 days was weaker (r = 0.17 and 0.16, respectively).

Transition weight was highly correlated with ADG from birth to transition (r = 0.97), which is expected given the mathematical relationship between both variables. It also showed moderate correlations with later body weight, suggesting that early growth contributes to, but does not fully determine, final body weight.

Table 3. Pearson correlation coefficients among body weights and average daily gains across growth stages.

Variables	BW at birth	BW at 40-46 days	BW at 219–225 days	ADG Birth to 40–46 days	ADG From 40–46 to 219–225 days	ADG from birth to 219-225 days
BW at birth	1					
BW at 40-46 days	0.507**	1				
BW at 219–225 days	0.175**	0.333**	1			
ADG Birth to 40–46 days	0.341**	0.965**	0.339**	1		
ADG From 40–46 to 219–225 days	0.140*	0.261**	0.993**	0.270**	1	
ADG from birth to 219-225 days)	0.160**	0.321**	0.997**	0.343**	0.992**	1

Significance: $p < 0.05$ (*), $p < 0.01$ (**).

The very high correlations between ADG from transition to rearing and ADG from birth to rearing are expected, as both variables share body weight at 220 days in their calculation. Therefore, these associations should be interpreted cautiously, as they reflect mathematical dependency rather than independent biological processes.

Influence of litter size and parental effects on body weight and growth

Litter size effects

The relationship between litter characteristics—number born alive (NBA), number born dead (NBD), and total born (TB)—and growth parameters of female piglets (gilts) is presented in Table 4.

Significant negative correlations were observed between litter size (NBA and TB) and birth weight ($r = –0.27$ and $–0.29$, respectively; $p < 0.01$), indicating that piglets originating from larger litters tended to have lower birth weights. Total born (TB) was also negatively correlated with transition weight ($r = –0.15$, $p < 0.01$).

In addition, the number of stillborn piglets (NBD) showed a weak negative association with transition weight ($r = –0.12$, $p < 0.05$). No significant correlations were detected between litter size variables and body weight at 220 days or average daily gain (ADG) during later growth phases.

Table 4. Pearson correlation coefficients between litter characteristics and growth parameters. Number born alive NBA, stillborn NBD, and total bornTB.

Variable	Birth weight	Transition weight	Weight 220 d	ADG Birth to 40–46 days	ADG From 40–46 to 219–225 days	ADG from birth to 219-225 days)
NBA	–0.273**	–0.100	–0.024	–0.048	–0.018	–0.021
NBD	–0.064	–0.116*	0.036	–0.084	0.048	0.047
TB	–0.289**	–0.146**	–0.008	–0.082	0.003	–0.001

Significance: $p < 0.05$ (*), $p < 0.01$ (**).

Maternal and paternal effects

Linear mixed-effects models were used to partition variance components attributable to sire and maternal/litter-level effects for each growth trait (Table 5).

A substantial maternal/litter-level variance component was detected for birth weight, accounting for approximately 40% of the total phenotypic variance. This contribution progressively declined with age, representing approximately 18% of variance at transition weight and 10% at 220 days. In contrast, sire-related variance components were small across all traits and did not reach statistical significance. The proportion of total variance attributable to sire remained below 3% at all developmental stages. The estimated narrow-sense heritability based on the paternal component was extremely low for all the weights ($h^2 \approx 0.006$; 0.08 and 0.13). and it was not statistically significant.

Residual variance increased with age and represented the largest proportion of total phenotypic variability at 220 days, indicating increasing individual-level variation as animals matured.

Collectively, these results indicate that early growth variability is predominantly influenced by maternal and shared litter-level factors, whereas individual environmental variability becomes increasingly important during later growth phases.

Table 5. Variance components estimated by linear mixed-effects models (REML) for growth traits, including sire and maternal/litter-level random effects.

Trait	Maternal variance (%)	Paternal variance (%)	Heretability Paternal h2
Birth weight	39.9	0.15	0.006
Transition weight	18.2	2.0	0.08
220-day weight	10.5	3.1	0.13

The results indicate that early growth performance in gilts is strongly influenced by maternal and litter-level factors, particularly at birth. However, as animals age, these effects progressively diminish, and individual-level environmental variability becomes the primary driver of phenotypic differences. No strong evidence of additive paternal genetic contribution was detected under the present experimental design.

Proportion of females within the litter and early gilt selection

The proportion of females within the litter was not significantly correlated with birth weight ($r = 0.03$, $p = 0.52$), transition weight ($r = –0.03$, $p = 0.56$), or ADG from birth to 40–46 days ($r = –0.07$, $p = 0.18$), indicating no detectable association between litter sex ratio and early growth performance.

Total litter size (TB) was negatively correlated with birth weight ($r = –0.289$, $p < 0.01$), confirming that piglets born in larger litters tended to have lower birth weights. Birth weight was positively associated with the selection ratio ($r = 0.265$, $p < 0.01$), indicating that heavier piglets were more likely to be selected as replacement gilts.

Total litter size was also negatively correlated with selection ratio ($r = –0.243$, $p < 0.01$) and with the proportion of females within the litter ($r = –0.302$, $p < 0.01$).

The selection ratio within each litter showed positive correlations with birth weight ($r = 0.26$, $p < 0.001$), transition weight ($r = 0.17$, $p < 0.001$), and overall ADG ($r = 0.16$, $p < 0.001$), indicating that litters with a higher proportion of selected females tended to present greater average growth performance (Table 6).

Table 6. Pearson correlation coefficients between litter variables, sex ratio, selection ratio, and birth weight.

Variable	TB	Female ratio	Selection ratio	Birth weight
TB	1			
Female ratio	–0.302**	1		
Selection ratio	–0.243**	–0.134**	1	
Birth weight	–0.289**	0.025	0.265**	1

Predictive Modeling of Transition Phase using machine learning techniques

Out of 520 females weighed at birth, 346 (67%) reached the transition phase, while 174 (33%) did not. Animals that failed to reach this phase were not lost by mortality but were instead redirected to other production units. These females had a significantly lower average birth weight (1.35 ± 0.02 kg) compared with those that reached transition (1.40 ± 0.01 kg; $p = 0.02$). This supports the notion that lower birth weight delays post-weaning growth and prolongs the time required to reach the minimum transfer weight.

Table 7. Performance metrics of Logistic Regression and Random Forest models for predicting the transition phase in female piglets.

Model	AUC	Classification Accuracy	Precision	Specificity
Random Forest	0.767	0.713	0.719	0.657
Logistic Regression	0.638	0.624	0.642	0.571

To explore the determinants of this outcome, logistic regression and Random Forest models were built using Orange Data Mining v39. Predictors included birth weight, total born (TB), number born alive (NBA), number born dead (NBD), female ratio, and selection ratio. The Random Forest model clearly outperformed the logistic regression in all evaluated metrics (AUC, classification accuracy, precision, and specificity), achieving an AUC of 0.77 versus 0.64 for logistic regression (Table 7 and Figure 1). This indicates that the non-linear Random Forest model captured additional interactions between litter characteristics and genetic or management factors that the linear logistic regression could not.

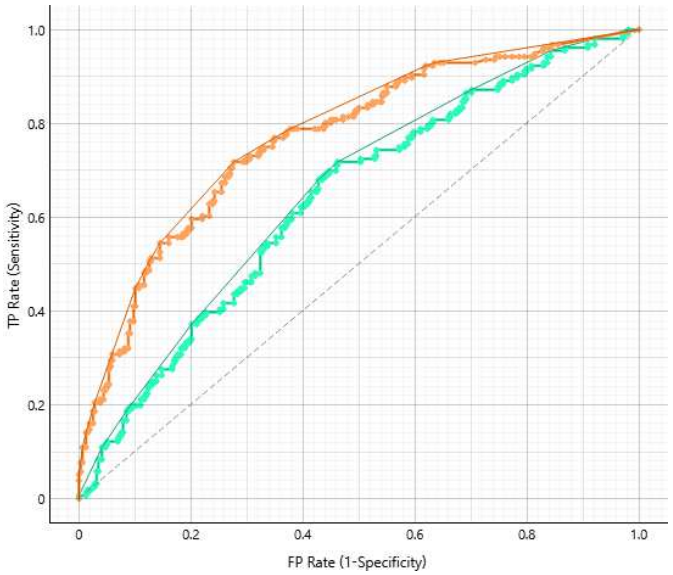


Figure 1. Area under the curve (AUC) for Logistic Regression (green) and Random Forest models (orange) for predicting the transition phase in female piglets.

The logistic regression coefficients confirmed that birth weight was the most influential predictor of reaching the transition phase (β = 0.51; OR = 1.66). Each additional kilogram of birth weight increased the odds of reaching transition by approximately 66%. In contrast, litter-size variables showed modest negative effects: each additional liveborn or total piglet reduced the odds of transition by about 3–4% (OR ≈ 0.96–0.97). The number of stillborn and the female ratio had negligible influence, while the selection ratio had a small positive effect (β = 0.02; OR = 1.02), suggesting that improved genetic or management selection slightly enhanced the probability of transition (table 8). The AUC of 0.64 for this model suggests biologically coherent but limited predictive power, reflecting the complexity of survival determinants in early pig development.

Table 8. Logistic regression coefficients and odds ratios for predictors of reaching the transition phase.

Variable	β	OR = exp(β)
Birth weight (kg)	+0.5091	1.664
NBA (number born alive)	−0.0291	0.971
NBD (number born dead)	−0.0085	0.992
TB (total born)	−0.0376	0.963
Female ratio	−0.0064	0.994
Selection ratio	+0.0213	1.022

Variable-importance analysis from the Random Forest model reinforced these findings. Birth weight was again the dominant factor (importance = 0.423), followed by the female ratio (0.200) and total born (0.108) (Table 9). The number born alive and stillborn had minor contributions (0.087 and 0.075, respectively). This pattern suggests that, beyond the direct influence of individual birth weight, the structure of the litter—particularly sex composition—may interact non-linearly with growth performance and survival probability. When the predicted probabilities were visualized (Figure 2), the Random Forest model distinguished clearly between animals that reached transition and those that did not, whereas logistic regression showed greater overlap between the two classes.

Table 9. Variable importance rankings from the Random Forest model for predicting transition phase attainment.

Variable	Importance (Random Forest)
Birth weight (kg)	0.423
Female ratio	0.200
TB (total born)	0.108
Selection ratio	0.106
NBA (number born alive)	0.087
NBD (number born dead)	0.075

Taking both models consistently identify birth weight as the principal determinant of transition success, while the Random Forest further detects subtle interactions involving litter composition and selection intensity. From a biological and production standpoint, these results highlight the importance of managing prenatal and early postnatal conditions that optimize birth weight and litter uniformity, as these factors have the strongest impact on post-weaning viability and progression to the next production stage.

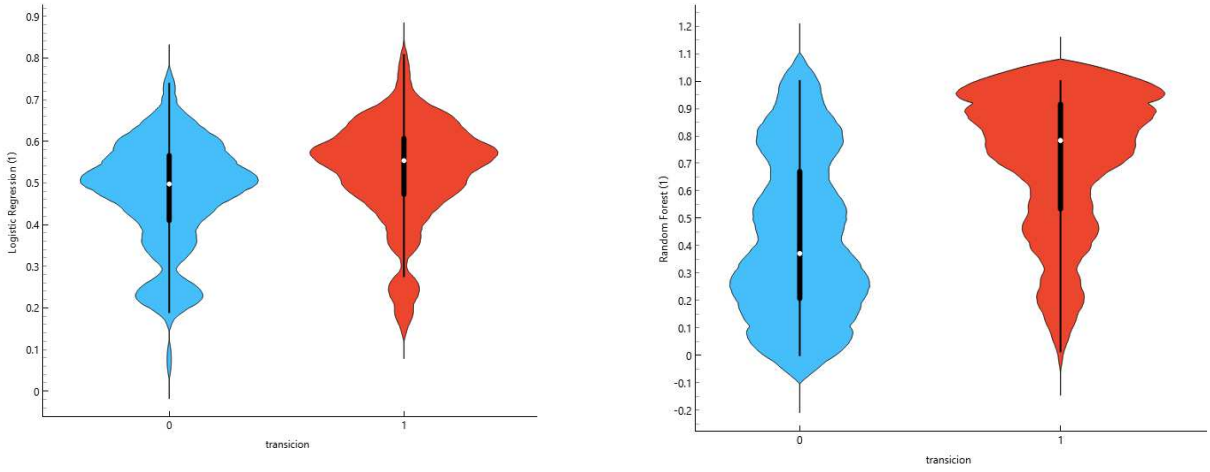


Figure 2. Predicted probabilities to reach the transition phase (red) or not (blue) by Logistic regression model (left) or Random Forest model (right).

Predicting which factors affect whether a young replacement sow reaches her first mating

We analyzed performance and growth records of gilts followed from birth to potential first mating. The target variable indicated whether an individual reached first insemination (1 = yes, 0 = no). Eleven predictors were included: birth weight, litter size traits (total born, born alive, born dead), female ratio, selection ratio, transition weight, average daily gain (ADG) during different phases (birth–transition, transition–mating, and transition only), and body weight at 220 days.

Logistic regression and Random Forest models were applied using stratified 10-fold cross-validation in Orange Data Mining v3.9. Model performance metrics are presented in table 10.

Table 10. Performance metrics of Logistic Regression and Random Forest models for predicting whether gilts reach first mating.

Model	AUC	Classification Accuracy	Precision	Specificity
Random Forest	0.740	0.783	0.770	0.583
Logistic Regression	0.515	0.709	0.515	0.277

The Random Forest model outperformed the logistic regression in all metrics (Table 10). The logistic regression showed little discriminative power (AUC ≈ 0.5), suggesting that

relationships between growth traits and reproductive success were non-linear and better captured by tree-based models. The Random Forest achieved moderate-to-good predictive capacity, indicating that early-life growth variables can meaningfully predict whether gilts reach the first insemination.

The regression model identified birth weight, transition weight, and ADG from birth to transition as the main positive predictors of reproductive success, While the weight at 220 days is inversely related (Table 11). Each 1 kg increase in birth weight raises the odds of reaching first mating by 71%, while a 1 kg increase at transition weight increases the probability in 46%. On the contrary, a 1 kg increase at the age of 220 days, reduces the probability of reaching the first mating in 13%.

Table 11. Logistic regression coefficients and odds ratios for predictors of first mating attainment in gilts.

Variable	β	OR = exp(β)
Birth weight	+0.539	1.71
Transition weight	+0.377	1.46
ADG (birth–transition)	+0.042	1.04
Body weight at 220 days	−0.141	0.87

Random Forest variable ranking corroborated the logistic regression results while revealing additional non-linear relationships. ADG from birth to transition was the most influential predictor (importance = 0.282), followed by ADG from transition to mating (0.173), birth weight (0.103), female ratio (0.084), and transition weight (0.082). Other variables, including total born, born alive, and body weight at 220 days, contributed less (<0.08).

The Random Forest model's higher AUC demonstrates that complex interactions among growth phases and management factors underlie the attainment of first mating, rather than simple additive effects. From a practical standpoint, these findings underscore the importance of monitoring and managing early growth trajectories — from birth through transition — to ensure that gilts reach first mating at an optimal physiological and chronological stage.

Discussion

The present study evaluated early-life growth traits and litter characteristics as predictors of gilt progression through key developmental stages, specifically transition attainment and first mating success under commercial production conditions. Birth weight was identified as the most consistent predictor of subsequent growth performance and reproductive progression. Secondary yet biologically meaningful influences were exerted by litter-level characteristics, including litter size and female proportion. Mixed-effects modeling revealed that maternal and shared environmental factors accounted for a substantial proportion of early growth variance, with a declining influence as animals matured. In contrast, additive sire effects were comparatively small. Complementary random forest modeling revealed non-linear interactions among predictors and provided moderate discriminative capacity (AUC up to 0.77 for transition and 0.74 for first mating), supporting the integration of predictive analytics into gilt management strategies. This study supports a shift from descriptive herd-level management toward individualized predictive reproductive management in commercial swine systems.

Maternal and paternal effects

The substantial maternal variance component observed at birth (~40%) confirms the dominant influence of maternal and shared environmental effects on early growth. These

factors are theorized to reflect uterine capacity, placental efficiency, litter size, colostrum intake, and early nursing conditions, as previously described (18, 19). The maternal contribution exhibited a decline in proportion with age, from 18.2% at transition to 10.5% at 220 days. This decline suggests a reduction in common litter effects as the gilts matured and individual-specific factors became more dominant.

Conversely, sire variance components were found to be negligible and statistically non-significant across the examined traits. While the estimated sire contribution exhibited a slight increase with age (0.15% at birth to 3.1% at 220 days), heritability estimates remained low (0.00–0.13). However, it is imperative to exercise caution when interpreting these values, as early-life traits are profoundly influenced by maternal covariance and environmental uniformity within commercial systems. Under the genetic structure and management conditions of this population, maternal and environmental factors explained a substantially larger proportion of phenotypic variance in early growth than additive sire effects.

The mixed-effects framework appropriately accounted for the hierarchical structure of the data (gilts nested within litters and sows) and enabled robust partitioning of variance components, thereby strengthening inference regarding biological sources of variability.

Birth Weight and Growth Trajectories

The consistent positive correlations observed among body weights and average daily gains across growth intervals provide evidence that gilts with higher birth weights tend to maintain superior growth performance throughout development. However, the decreasing strength of these associations over time suggests a form of compensatory growth, whereby lighter piglets at birth partially overcome their initial disadvantage during later stages. This pattern aligns with the findings reported by (11, 12), who also documented a decline in the predictive value of birth weight as animals approach sexual

maturity. Consequently, while birth weight remains a useful early indicator, later metrics such as transition weight and ADG during rearing may provide more reliable predictors of final body weight under commercial conditions.

From a pragmatic perspective, this underscores the notion that, while birth weight should persist as a fundamental selection criterion, subsequent metrics (e.g., transition weight, ADG during rearing) might confer independent predictive value and should be integrated into standard monitoring protocols on farms.

Litter Size, Sex Ratio, and Selection Outcomes

As anticipated, litter size demonstrated a negative correlation with individual birth weight, aligning with the concepts of intrauterine competition and uterine crowding constraints previously outlined in scholarly literature (13, 14). However, no association was detected between litter size and body weight at 220 days, suggesting that post-weaning growth compensation under standardized nutritional management may mitigate early weight disadvantages.

Litter uniformity, defined as the proportion of selected females within a litter, exhibited a robust correlation with augmented birth and transition weights, as well as heightened ADG. This finding aligns with prior research indicating that within-litter homogeneity has a positive impact on survival, puberty onset, and reproductive potential (1, 4, 8). It is hypothesized that uniform litters are indicative of superior uterine function and balanced nutrient allocation during gestation, thereby promoting consistent postnatal growth. Consequently, the assessment of litter uniformity can serve as a practical complement to individual weight measurements in gilt selection protocols.

With regard to the sex ratio, no direct correlation with growth traits was identified. However, extant research indicates that female offspring gestated in male-biased litters may be exposed to elevated intrauterine androgen concentrations, which could

potentially influence reproductive physiology (15-17). Although not evaluated in this study, future research incorporating physiological markers, such as anogenital distance (AGD) or anti-Müllerian hormone (AMH) concentrations, may elucidate the relationship between prenatal endocrine environment and reproductive development.

Predictive Modelling and Non-Linear Effects

The integration of Random Forest modeling with conventional mixed-effects and regression analyses yielded complementary insights. Logistic regression identified birth weight as the primary predictor of transition and first mating success. Random Forest models revealed additional non-linear interactions involving litter structure variables, including female ratio and selection proportion.

The predictive discrimination was moderate (AUC 0.74–0.77), indicating that these models are suitable for probabilistic ranking rather than deterministic classification. However, this level of performance is operationally relevant in commercial systems, where incremental improvements in selection efficiency can translate into meaningful economic gains.

Machine learning approaches, therefore, represent a valuable analytical extension to traditional parametric models, particularly in complex biological systems characterized by hierarchical data structures and non-linear relationships. Machine learning is an evolving field that has been employed for the purpose of predicting reproductive outcomes in sows (20, 21) and monitoring herd health (22)

Study limitations

When interpreting the present findings, it is essential to acknowledge several limitations. First, although the sample size (510 gilts from 77 litters) is representative of a commercial production cohort, it may limit the detection of small genetic effects and reduce the generalizability of variance component estimates. Secondly, data were obtained from

farms operating under the same management system and genetic line, which restricts extrapolation to herds with different nutritional programs, health status, housing systems, or genetic backgrounds. Thirdly, the study was conducted under standardized commercial conditions, which, while enhancing internal consistency, may mask environmental variability present in more heterogeneous production systems. Finally, the assessment of endocrine or physiological biomarkers associated with ovarian reserve and reproductive maturation (e.g., anti-Müllerian hormone concentrations or anogenital distance) was not conducted. The incorporation of these biomarkers into future studies would facilitate a more mechanistic interpretation of the relationship between early growth dynamics and reproductive outcomes. Despite these limitations, the longitudinal design and integration of hierarchical modeling with predictive analytics provide robust evidence supporting the relevance of early-life growth traits in gilt developmental progression.

Practical Management Implications

Collectively, these results support the implementation of a structured on-farm gilt management strategy that integrates systematic early-life phenotypic monitoring with data-driven predictive tools. The systematic documentation of birth and transition weights should be an integral element of gilt selection protocols, as these metrics offer reliable early indicators of developmental potential. The incorporation of metrics quantifying litter uniformity and longitudinal growth trajectories has the potential to further refine replacement decisions by facilitating the identification of gilts exhibiting consistent performance patterns. Furthermore, the early detection of suboptimal growth trajectories facilitates the implementation of targeted management interventions, such as customized nutritional programs or environmental modifications for at-risk animals. These interventions have the potential to modify developmental outcomes before critical reproductive milestones are attained. The incorporation of machine learning algorithms into herd management software provides an added benefit by facilitating real-time,

probabilistic decision-making processes based on multivariate data. The integration of these approaches, which encompasses the linkage of hierarchical biological determinants with individual-level predictive analytics, is congruent with the objectives of precision livestock production (23). These objectives include the enhancement of reproductive efficiency, the optimization of resource allocation, and the control of operational costs.

Beyond the consideration of individual growth performance, the optimization of gilt selection through the utilization of early predictive indicators may contribute to the enhancement of herd health sustainability. The reduction of premature culling and the augmentation of sow longevity serve to stabilize herd structure, decrease replacement pressure, and diminish the proportion of immunologically naïve animals entering the breeding population (24). This may contribute to greater epidemiological stability, reduced non-productive days, and improved overall herd resilience under commercial conditions (25).

Conclusions

Early growth performance, particularly birth weight, emerged as the most robust predictor among the traits evaluated for gilt developmental progression and reproductive success under commercial conditions. Heavier piglets consistently exhibited higher body weights, superior average daily gains, and greater likelihood of reaching both the transition and first mating stages. Maternal and litter-level factors explained a substantial proportion of early growth variability, with maternal effects accounting for approximately 40% of birth weight variance, whereas additive sire effects were limited within this population.

Litter uniformity emerged as a significant predictor of selection success, while larger litter sizes were associated with diminished individual birth weights, indicative of inherent

limitations in uterine capacity. These results underscore the pivotal function of prenatal and early postnatal environments in influencing the developmental trajectories of gilt.

The integration of Random Forest modeling enabled the detection of non-linear interactions among growth and litter variables and provided moderate predictive accuracy for individual outcomes. The integration of traditional mixed-effects modeling with individual-level prediction facilitates the implementation of precision management strategies, encompassing targeted nutritional support, refined replacement selection, and the early identification of gilts at risk of suboptimal progression.

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Conflict of Interest

The authors declare no conflict of interest.

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