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Abstract

This study developed and internally evaluated a two-input candidate model for estimating VCS2000-derived belly fat percentage (BFP) in slaughterhouses without automated carcass evaluation equipment. Data from 1,753 LYD (Landrace $\times$ Yorkshire $\times$ Duroc) pigs slaughtered in Korea were analyzed. Hot carcass (HC) traits were obtained using VCS2000, whereas corresponding chilled carcass (CC) backfat traits were measured manually. Multiple linear regression models were assessed using influence diagnostics, sensitivity analyses, cross-validation, and comparisons with machine learning algorithms. In HC measurements, BFP was strongly associated with multifidus muscle middle backfat thickness (MBT) and backfat thickness at the first thoracic vertebra (FTBT). Under the CC/manual condition, the MBT association remained relatively strong, whereas the FTBT association was weaker. The HC full and reduced models showed no substantial difference in explanatory or cross-validated predictive performance, whereas the CC/manual reduced model showed lower performance. The evaluated machine learning methods did not meaningfully outperform multiple linear regression. Measurement concordance was lower for FTBT than for MBT and grading backfat thickness, although the effects of carcass state and measurement procedure could not be separated. These findings provide a basis for further development of the two-input model as a candidate approach for BFP estimation.

Keywords : Pork belly, Belly fat percentage, Backfat thickness, VCS2000, Multiple linear regression

Introduction

Carcass grading is a central framework in the Korean swine industry because it supports transactions, processing decisions, and price determination [1]. Carcass weight and backfat thickness are the principal grading indicators because they are easy to measure and reflect the overall fattening status of a carcass [2]. However, these indicators summarize the whole carcass and do not fully describe the quality or composition of individual primal cuts [3].

Fat deposition and the quality attributes valued by consumers differ among pork cuts [4]. Pork belly is widely consumed in Korea [7], and differences in fat proportion and distribution can contribute to variation in juiciness, flavor, texture, and commercial characteristics among carcasses within the same grade [5,6]. Such variation can affect visual acceptability, sorting, trimming, processing yield, distributor preferences, and compliance with market specifications. BFP therefore provides information specific to the belly that complements conventional grading traits [7,8]. Backfat thickness has been examined as a predictor of primal cut value [9], and non-destructive scanning systems have been used to estimate carcass composition and lean yield [10,11,12]. However, these systems require specialized equipment and technical expertise and may not be available in many slaughterhouses. Therefore, a regression equation derived from a small number of anatomical measurements could provide a more accessible method for estimating pork belly fat percentage. Previous research using VCS2000 examined associations among BFP estimated by the system, the visual fat level of pork belly, and distributor preferences [8], but it did not develop a model based only on a limited number of anatomically defined measurements of backfat thickness. The present study therefore aimed to develop and internally evaluate a candidate model using MBT and FTBT as a basis for future estimation in slaughterhouses without automated systems and to determine whether these measurements retained most of the explanatory and predictive information provided by the full model.

Materials and Methods

2.1. Animals

LYD (Landrace × Yorkshire × Duroc) crossbred pigs slaughtered at a commercial abattoir located in Eumseong-gun, Chungcheongbuk-do, Korea, between July 2024 and January 2025, were used in this study. Primary carcass grading was performed based on carcass weight and backfat thickness according to the official grading criteria for porcine carcasses (Notification No. 2023-102 of the Ministry of Agriculture, Food and Rural Affairs, Chapter 3, Article 9). A total of 1,753 pigs,

consisting of gilts (n = 892) and barrows (n = 861) graded as 1+, 1, or 2, were included in the analysis, while carcasses classified as off-grade were excluded.

2.2. Carcass measurements

To evaluate carcass characteristics, measurements were obtained under two conditions. Immediately after slaughter, the left split hot carcass (HC) was imaged and analyzed using the VCS2000 automated carcass analysis system. After chilling, backfat thickness at the corresponding anatomical sites on the chilled carcass (CC) was measured manually with a ruler. The two procedures targeted corresponding anatomical measurands (the linear thickness of subcutaneous backfat at corresponding sites) but differed in both measurement modality and carcass state. Accordingly, their results were compared as HC/VCS2000 and CC/manual measurement conditions rather than as a controlled evaluation of chilling alone.

The anatomical sites are illustrated in Figure 1. Multifidus muscle middle backfat thickness (MBT) was measured at the middle of the multifidus muscle. Grading backfat thickness (GBT) was calculated as the mean of backfat thickness at the 11th–12th thoracic vertebral site and at the junction between the last thoracic vertebra and the first lumbar vertebra. Backfat thickness at the first thoracic vertebra was designated FTBT. Figure 1 identifies these sites as A, B, C, and D, respectively, with GBT calculated from B and C.

2.3. VCS2000

The VCS2000 (E+V Technology GmbH, Oranienburg, Germany) is an integrated system for carcass image acquisition and analysis. It comprises monochrome and color cameras, lighting and background modules, carcass positioning guides and holders, a control unit, proprietary vision software, and an analysis computer. Pig carcasses were split longitudinally, and forequarter and hindquarter images were acquired and transmitted to the system computer for analysis by software.

The VCS2000 outputs considered in this study comprised 29 carcass traits: four backfat thickness traits (GBT, MBT, FTBT, and fat thickness 10 cm inside the back); weights and corresponding lean

meat weights for seven primal cuts (rib, shoulder blade, shoulder picnic, tenderloin, loin, belly, and ham; 14 traits); three additional cut weights (shoulder shank, hind shank, and skirt meat); two outputs related to the belly (belly fat weight and belly yield); and six whole carcass composition outputs (total pork skin weight, total fat weight, total bone weight, total meat yield, total lean meat weight, and lean meat percentage). Carcass weight was recorded during official grading and, together with these 29 outputs, formed the 30 candidate predictors examined in the initial correlation screening. BFP derived from VCS2000 was not included among the candidate predictors and was analyzed separately as the dependent variable and operational reference outcome.

The detailed proprietary algorithms used to generate the VCS2000 composition and yield outputs were not available to the authors. In particular, whether MBT, FTBT, or other backfat thickness outputs were directly incorporated into the VCS2000 BFP calculation could not be confirmed, and the possibility of shared information between the predictors and the outcome derived from VCS2000 cannot be excluded. Thus, these outputs are not described as independently measured anatomical or chemical reference values.

2.4. Statistical analysis

All statistical analyses were performed using the scikit-learn library in Python (Python version 3.13, Python Software Foundation, USA). Pandas was used for data handling; NumPy and SciPy for numerical calculations; statsmodels for ordinary least squares (OLS) regression and Cook's distance; and scikit-learn and XGBoost for cross-validation and the algorithm comparison. BFP derived from VCS2000 was used as the dependent variable in all models.

Pearson's correlation coefficients were calculated between BFP derived from VCS2000 and 30 candidate predictors, comprising carcass weight and 29 carcass traits derived from VCS2000. BFP was not included among the candidate predictors. The Pearson correlation coefficient between traits measured by VCS2000 and BFP was calculated as follows:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}$$

Following published guidance [13], values of 0.70 or higher were considered to indicate strong descriptive associations and were therefore used as the feature-selection criterion in this study. Subsequent model development focused on carcass weight (CW), GBT, MBT, and FTBT because CW is routinely obtained during grading, whereas the three thickness traits are anatomically defined and potentially measurable on a split carcass. Differences among weight classes were assessed using one-way analysis of variance followed by Tukey's honestly significant difference test. Because HC and CC measurements were obtained from the same carcasses, within each class comparisons between the HC/VCS2000 and CC/manual conditions were analyzed as paired comparisons. Statistical significance was declared at $p < 0.05$.

2.4.1 Models

Three OLS models were evaluated. The HC full model included CW, GBT, MBT, and FTBT. The HC reduced model included MBT and FTBT, while the CC reduced model used manually measured MBT and FTBT. All 15 possible nonempty subsets of the four HC candidate predictors were compared on the common sample of 1,664 carcasses using the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Because only four candidate predictors were considered, all possible subsets could be enumerated directly, avoiding the path dependence of stepwise, forward, and backward selection procedures. LASSO, ridge, and Elastic Net were not used as the primary selection strategy because the predictor space was small relative to the sample size and the objective was to compare an explicit reduced equation with the full benchmark rather than to stabilize a model with many predictors. The MBT and FTBT model was evaluated as a parsimonious candidate motivated by measurement simplicity, not assumed to be the statistically optimal subset.

Influential observations were screened separately for each model using a single application of Cook's distance $> 4/n$, where n was the initial number of observations used to fit the corresponding model ($n = 1,753$) [14,15]. This heuristic identifies potentially influential cases but does not establish biological abnormality or measurement error. This procedure excluded 83 observations from the HC full model, 89 from the HC reduced model, and 100 from the CC reduced model, producing final analytical

samples of 1,670, 1,664, and 1,653, respectively. Screening was not iterated after refitting. Characteristics of the model-specific influential groups and sensitivity analyses before and after screening were summarized in the Supplementary Tables and Figures. Regression diagnostics were conducted on the final analytical sample for each model because those samples were used to fit the equations reported after screening based on Cook's distance. Residuals versus fitted values, scale-location plots, and quantile–quantile plots were examined, and residual skewness, standardized residuals, the Breusch–Pagan test, and the Ramsey Regression Equation Specification Error Test (RESET) were evaluated. HC3 standard errors robust to heteroscedasticity were calculated as a robustness check. Separate sensitivity analyses compared coefficients and predictive performance before and after screening and evaluated the equations fitted after screening on all 1,753 observations. Multicollinearity was assessed using variance inflation factors (VIFs), calculated as $VIF_j = 1/(1-R_j^2)$, where R_j^2 is obtained by regressing predictor j on the remaining predictors. Values above 5 or 10 are often treated as indications of potentially important variance inflation, but such thresholds are contextual and should not be interpreted mechanically [16,17]. VIF is not a significance test and does not establish biological independence or nonredundant predictive information. Internal predictive performance was assessed using the same five shuffled folds for the HC full and reduced models on all 1,753 observations before screening based on Cook's distance (random state = 42), consistent with established principles of cross-validation [18,19]. This procedure evaluates internal predictive stability within the present population and should not be interpreted as independent external validation. Given the previous use of flexible algorithms for predicting pig body composition when richer imaging inputs are available [20], multiple linear regression was compared with Random Forest (RF), XGBoost, support vector regression with a radial basis function (RBF-SVR), and a multilayer perceptron (MLP) to determine whether these algorithms improved accuracy when the same two inputs were used. All 1,753 observations were evaluated using identical outer five-fold splits. Hyperparameters were selected by inner five-fold cross-validation using root mean squared error

(RMSE), and all preprocessing was fitted within the training folds. The benchmark used Python 3.12.13, scikit-learn 1.7.1, and XGBoost 3.0.2; complete search ranges and settings selected for each fold are provided in the Supplementary Tables and Figures. Consistency between measurement conditions was evaluated using paired HC and CC observations from all 1,753 carcasses. For GBT, MBT, and FTBT, Pearson's r , the mean difference (CC–HC), 95% limits of agreement, and Lin's concordance correlation coefficient (CCC) were calculated. These analyses quantify agreement between the two measurement conditions and cannot separate the effects of carcass state from those of measurement procedure.

Results and Discussion

3.1. Backfat thickness characteristics across carcass weight classes

GBT, MBT, and FTBT generally increased across the 70–79, 80–89, and 90–99 kg carcass weight classes (Tables 1–3), consistent with continued fat deposition during finishing [21,22]. Because the 100–109 kg class included only eight carcasses, the results for this group should be interpreted with caution. In the paired analyses, GBT differed significantly between the HC/VCS2000 and CC/manual conditions in all four weight classes ($p < 0.05$). MBT differed significantly in the 70–79 and 80–89 kg classes ($p < 0.05$), but not in the 90–99 and 100–109 kg classes ($p > 0.05$). FTBT also differed significantly in all four weight classes ($p < 0.05$). Although CC FTBT in the 100–109 kg class was numerically lower than that in the 90–99 kg class, Tukey's test showed that this difference was not statistically significant ($p > 0.05$), and it was therefore not interpreted as evidence of a nonlinear biological response.

These HC–CC contrasts reflect the simultaneous change in carcass state and measurement procedure. Previous research indicates that carcass processing and postmortem conditions can alter pork belly thickness, shape, firmness, and cohesiveness [23,24,25], while measured backfat depth can differ according to anatomical position and measurement procedure [26,27]. Accordingly, it should be noted that the observed values may vary depending on postmortem moisture loss, tissue contraction,

regional changes in muscle and fat, measurement-site reproducibility, ruler orientation, and other sources of variation specific to each measurement method.

3.2. Associations between carcass traits and BFP derived from VCS2000

Correlations between BFP and the 30 candidate predictors are shown in Figure 2. Under the HC/VCS2000 condition, BFP was strongly associated with MBT ($r = 0.82$) and FTBT ($r = 0.80$), moderately associated with GBT ($r = 0.58$), and weakly associated with CW ($r = 0.28$) (Figure 3A). Under the CC/manual condition, the MBT–BFP correlation remained relatively high ($r = 0.73$), the GBT–BFP correlation was similar ($r = 0.57$), and the FTBT–BFP correlation was markedly lower ($r = 0.40$) (Figure 3B). A previous study likewise reported strong associations between VCS2000-derived BFP and MBT and FTBT but did not develop or validate a two-input prediction model [8]. MBT, FTBT, and the two sites used to calculate GBT are spatially separated along the carcass (Figure 1). Together with the known regional heterogeneity of porcine fat deposition [4,28], this provides a plausible anatomical context for the stronger observed associations of MBT and FTBT with BFP than of composite GBT. However, these data do not establish a direct anatomical mechanism. Moreover, because the proprietary VCS2000 BFP algorithm was unavailable, the strong correlations may reflect regional biological relationships, shared algorithmic information, or both. The CC/manual results show only that predictive information was recoverable from separately acquired measurements of the same anatomical traits; they do not exclude shared information with the outcome derived from VCS2000.

3.3. Full and reduced regression models

Before screening for influential observations, the HC full model containing CW, GBT, MBT, and FTBT yielded $R^2 = 0.73$ and mean squared error (MSE) = 4.85 (Supplementary Table S8A). After 83 influential observations were excluded, the model was fitted to 1,670 carcasses and yielded $R^2 = 0.79$ and MSE = 3.42 (Table 4). The HC reduced model containing MBT and FTBT also yielded $R^2 = 0.73$ before screening, with MSE = 4.93, and $R^2 = 0.79$ and MSE = 3.42 after 89 influential observations

were excluded (Table 5). Because the post-screening values were obtained from different samples, they were not directly compared. On the common sample of 1,664 carcasses, both the full and reduced models yielded $R^2 = 0.79$ at the reported precision, indicating no substantial difference in explanatory performance at that precision. A partial F-test ($p < 0.001$) and exhaustive AIC/BIC comparison favored the full model (Supplementary Table S7), indicating that CW and GBT made statistically detectable but small incremental contributions. Thus, the reduced model is presented as a parsimonious candidate, not as the statistically optimal model. The resulting HC two-variable reduced candidate equation was:

$$\text{BFP (\%)} = 10.13 + 0.55 \times \text{MBT (mm)} + 0.46 \times \text{FTBT (mm)}.$$

The CC/manual model using two variables yielded $R^2 = 0.55$ and $\text{MSE} = 8.19$ before screening. After 100 observations were excluded, the model fitted to 1,653 carcasses yielded $R^2 = 0.63$ and $\text{MSE} = 5.86$ (Table 6). The lower explanatory performance under the CC/manual condition cannot be attributed solely to chilling because measurement modality changed concurrently. Figure 4 illustrates the HC regression plane after screening.

3.4. Consistency of measurements between conditions

Paired HC–CC correlations were higher for GBT and MBT than for FTBT, with FTBT also showing the lowest concordance (Supplementary Table S9). The relatively high MBT concordance provides preliminary evidence that direct measurement can retain substantial information for at least one of the two reduced model inputs. In contrast, FTBT showed substantially lower concordance and remains the principal limitation related to measurement. Greater FTBT variability may have attenuated its association with BFP under the CC/manual condition, but the data cannot determine whether this arose from postmortem change, manual measurement variability, or both. These analyses do not constitute a conventional study comparing measurement methods because carcass state was not held constant.

3.5. Model diagnostics, sensitivity, and internal predictive validation

Screening based on Cook's distance identified 83, 89, and 100 influential observations in the HC full, HC reduced, and CC reduced models, respectively. The excluded observations contained no missing or negative measurements and overlapped the observed biological ranges; without replicate records, they could not be classified as measurement errors rather than biological variation. Their characteristics are reported in Supplementary Tables S2A and S2B. Screening materially improved fit within the retained samples, but the fitted relationships were stable. When the equations fitted after screening were reapplied to all 1,753 carcasses, both HC models yielded $R^2 = 0.73$ at the reported precision, indicating no substantial difference at that precision, whereas the CC reduced model yielded $R^2 = 0.54$. These values closely matched the corresponding unscreened values of 0.73, 0.73, and 0.55 (Supplementary Tables S3 and S8A).

Residual plots, standardized residuals, Breusch–Pagan tests, Ramsey RESET tests, and robust HC3 coefficient inference did not change the principal coefficient conclusions (Supplementary Table S1 and Supplementary Figures S1–S3). Fewer than 0.6% of observations in any final analytical sample had absolute standardized residuals greater than 3. For the unscreened HC and CC reduced models, RESET was not significant for the HC model ($p = 0.10$) but was significant for the CC model ($p = 0.04$) (Supplementary Table S6); this result did not translate into meaningful improvement by the evaluated nonlinear algorithms in nested cross-validation. VIF values ranged from 1.20 to 3.13 across the three models (Figures 5–7), and all were below 5, indicating no substantial variance inflation under the criterion used in this study. However, VIF thresholds are contextual, and these results do not establish biological independence or nonredundant predictive information.

In five-fold cross-validation using identical folds and all 1,753 carcasses, the HC full model yielded mean $R^2 = 0.73 \pm 0.02$, RMSE = 2.20 ± 0.15 , and mean absolute error (MAE) = 1.66 ± 0.06 ; the HC reduced model yielded $R^2 = 0.73 \pm 0.02$, RMSE = 2.22 ± 0.16 , and MAE = 1.66 ± 0.08 (Supplementary Table S8B). Thus, mean R^2 and MAE showed no substantial difference at the reported precision, and the RMSE difference was small. Under nested five-fold cross-validation using the same two inputs, RF and XGBoost performed below multiple linear regression, whereas RBF-SVR and MLP were essentially equivalent. No evaluated algorithm provided a meaningful accuracy

gain over linear regression (Supplementary Tables S4 and S5). These results represent internal validation in one population and do not establish external generalizability.

3.6. Proof of concept implementation

The HC two-variable reduced candidate equation was implemented in a proof-of-concept interface (Figure 8). Users enter MBT and FTBT measurements, and the interface calculates the estimated VCS2000-derived BFP. This implementation illustrates how the equation could be incorporated into a simple measurement-based workflow in slaughterhouses without automated carcass evaluation equipment. Further field evaluation is required to determine the accuracy, reproducibility, processing speed, and economic value of implementing the equation with manually collected HC measurements.

3.7. Study limitations and future validation

This study has several important limitations. First, BFP derived from VCS2000 was used as an operational reference outcome rather than an independently measured belly fat content. Because the proprietary algorithm was unavailable, shared information between backfat predictors and BFP cannot be excluded. A previous evaluation compared VCS2000-derived primal cut weights with dissected weights but did not validate the BFP output used here [29]. Second, the data were obtained from LYD pigs processed at one commercial facility over a limited temporal and geographic range; five-fold cross-validation therefore does not demonstrate transportability across breeds, production systems, slaughter conditions, or measurement systems. Third, manual HC measurements, replicate operator measurements, calibration between methods under the same carcass state, measurement time, training requirements, workflow effects, and economic outcomes were not evaluated.

Prospective validation should apply a fixed equation, without refitting or screening based on the outcome, to newly collected carcasses from multiple breeds, facilities, seasons, and operators. The validation design should include standardized manual HC measurements, prespecified anatomical landmarks and ruler orientation, replicate measurements within and between operators, and independent reference determination of belly fat content by standardized dissection or chemical

analysis. Performance should be evaluated using R^2 , RMSE, MAE, calibration intercept and slope, subgroup analyses, measurement time, throughput, training burden, and economic impact before field implementation is considered.

Conclusion

MBT and FTBT were strongly associated with VCS2000-derived BFP. Internal cross-validation showed that the HC reduced model retained most of the predictive performance of the full model containing CW and GBT, while the evaluated machine learning algorithms provided no meaningful improvement over multiple linear regression. Together, these findings support the HC reduced model as a parsimonious two-input candidate for further development as a BFP estimation method for slaughterhouses without automated carcass evaluation equipment.

However, carcass state and measurement procedure changed simultaneously, and FTBT showed relatively low concordance between the HC/VCS2000 and CC/manual conditions. Validation using manually collected HC measurements, independent reference measurements of belly fat content, and external populations is therefore required before field application.

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Tables

Table 1. Comparison of grading backfat thickness between hot and chilled carcasses across carcass weight classes¹⁾

Carcass weight (kg)	Hot carcass grading backfat thickness (mm)	Chilled carcass grading backfat thickness (mm)
70-79	16.98±3.30 ^{Bc} (210)	19.05±3.34 ^{Ac} (210)
80-89	19.48±3.43 ^{Bb} (1200)	21.38±3.38 ^{Ab} (1200)
90-99	21.52±3.83 ^{Ba} (335)	22.97±3.52 ^{Aa} (335)
100-109	23.25±2.31 ^{Ba} (8)	25.44±2.43 ^{Aa} (8)
Total	19.59±3.71 (1753)	21.42±3.57 (1753)

Values are presented as means ± standard deviations (n).

^{A-B} Different uppercase superscripts within the same row indicate significant differences between hot and chilled carcasses ($p < 0.05$).

^{a-c} Different lowercase superscripts within the same column indicate significant differences among carcass weight classes ($p < 0.05$).

¹⁾ Grading backfat thickness was measured by averaging the 11th–12th thoracic vertebra backfat thickness and the last thoracic vertebra–first lumbar vertebra backfat thickness.

Table 2. Comparison of multifidus muscle middle backfat thickness between hot and chilled carcasses across carcass weight classes

Carcass weight (kg)	Hot carcass multifidus muscle middle backfat thickness (mm)	Chilled carcass multifidus muscle middle backfat thickness (mm)
70-79	12.42±3.54 ^{Bc} (210)	13.24±3.50 ^{Ac} (210)
80-89	14.35±3.78 ^{Bb} (1200)	14.86±3.53 ^{Ab} (1200)
90-99	16.15±3.72 ^a (335)	16.33±3.58 ^a (335)
100-109	19.12±2.42 ^a (8)	17.25±2.55 ^{ab} (8)
Total	14.48±3.89 (1753)	14.96±3.64 (1753)

Values are presented as means ± standard deviations (n).

^{A-B} Different uppercase superscripts within the same row indicate significant differences between hot and chilled carcasses ($p < 0.05$).

^{a-c} Different lowercase superscripts within the same column indicate significant differences among carcass weight classes ($p < 0.05$).

Table 3. Comparison of first thoracic vertebra backfat thickness between hot and chilled carcasses across carcass weight classes

Carcass weight (kg)	Hot carcass first thoracic vertebra backfat thickness (mm)	Chilled carcass first thoracic vertebra backfat thickness (mm)
70-79	34.03±3.53 ^{A_c} (210)	29.20±5.33 ^{B_c} (210)
80-89	35.84±3.51 ^{A_b} (1200)	31.26±5.53 ^{B_b} (1200)
90-99	37.96±3.64 ^{A_a} (335)	32.59±5.93 ^{B_a} (335)
100-109	39.88±2.95 ^{A_a} (8)	28.75±5.60 ^{B_{a_{b_c}}} (8)
Total	36.05±3.71 (1753)	31.25±5.66 (1753)

Values are presented as means ± standard deviations (n).

^{A-B} Different uppercase superscripts within the same row indicate significant differences between hot and chilled carcasses ($p < 0.05$).

^{a-c} Different lowercase superscripts within the same column indicate significant differences among carcass weight classes ($p < 0.05$).

Table 4. Multiple linear regression model for predicting belly fat percentage in hot carcasses using CW, GBT, MBT, and FTBT as independent variables

Intercept (β_0)	Regression coefficient of carcass weight (β_1)	Regression coefficient of grading backfat thickness (β_2)	Regression coefficient of multifidus muscle middle backfat thickness (β_3)	Regression coefficient of first thoracic vertebra backfat thickness (β_4)	R^2	MSE ¹⁾
12.25	-0.04	0.08	0.51	0.46	0.79	3.42

Dependent variable: belly fat percentage derived from VCS2000 (%)

The model was fitted after excluding 83 influential observations identified using Cook's distance; final n = 1,670.

¹⁾ Mean Square Error

The intercept is expressed in BFP percentage points; the CW coefficient in BFP percentage points per kilogram; the GBT, MBT, and FTBT coefficients in BFP percentage points per millimeter; and MSE in squared BFP percentage points.

Table 5. Multiple linear regression model for predicting belly fat percentage in hot carcasses using MBT and FTBT as independent variables

Intercept (β_0)	Regression coefficient of	Regression coefficient of	R^2	MSE ¹⁾
	multifidus muscle middle backfat thickness (β_1)	first thoracic vertebra backfat thickness (β_2)		
10.13	0.55	0.46	0.79	3.42

Dependent variable: belly fat percentage derived from VCS2000 (%)

¹⁾ Mean Square Error

The intercept is expressed in BFP percentage points; the MBT and FTBT coefficients in BFP percentage points per millimeter; and MSE in squared BFP percentage points.

Table 6. Multiple linear regression model for predicting belly fat percentage in chilled carcasses using MBT and FTBT as independent variables

Intercept (β_0)	Regression coefficient of multifidus muscle middle backfat thickness (β_1)	Regression coefficient of first thoracic vertebra backfat thickness (β_2)	R^2	MSE ¹⁾
19.40	0.82	0.10	0.63	5.86

Dependent variable: belly fat percentage derived from VCS2000 (%)

¹⁾ Mean Square Error

The intercept is expressed in BFP percentage points; the MBT and FTBT coefficients in BFP percentage points per millimeter; and MSE in squared BFP percentage points.

Figures



Figure 1. Anatomical sites used for backfat thickness measurement, shown on a split pork carcass image acquired using the VCS2000 system. (A) Backfat thickness at the middle of the multifidus muscle (MBT); (B) backfat thickness at the 11th–12th thoracic vertebral site; (C) backfat thickness at the junction between the last thoracic vertebra and the first lumbar vertebra; and (D) backfat thickness at the first thoracic vertebra (FTBT).

Grading backfat thickness (GBT) was calculated as the mean of measurements B and C. The corresponding anatomical sites were used for manual measurements in chilled carcasses.

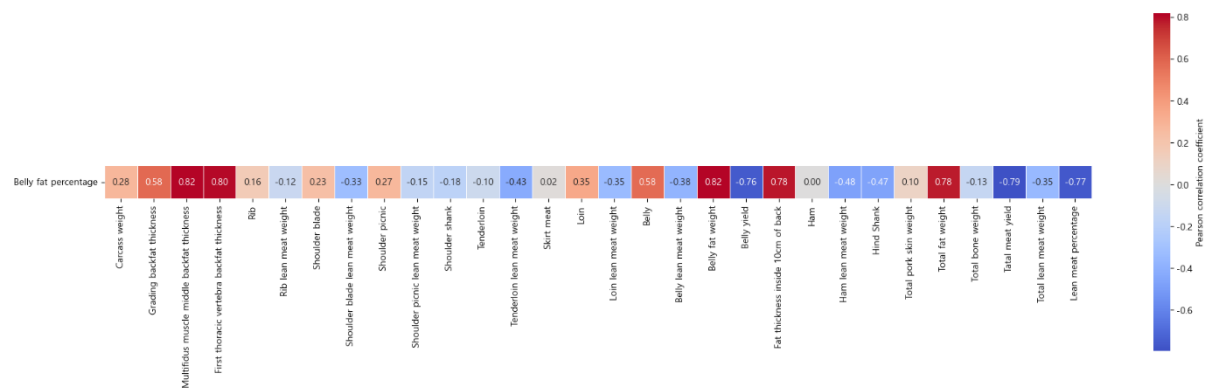


Figure 2. Heatmap showing Pearson's correlation coefficients between VCS2000-derived belly fat percentage and 30 candidate predictors comprising carcass weight and 29 VCS2000-derived carcass traits. Belly fat percentage was analyzed separately as the dependent variable and was not included among the candidate predictors.

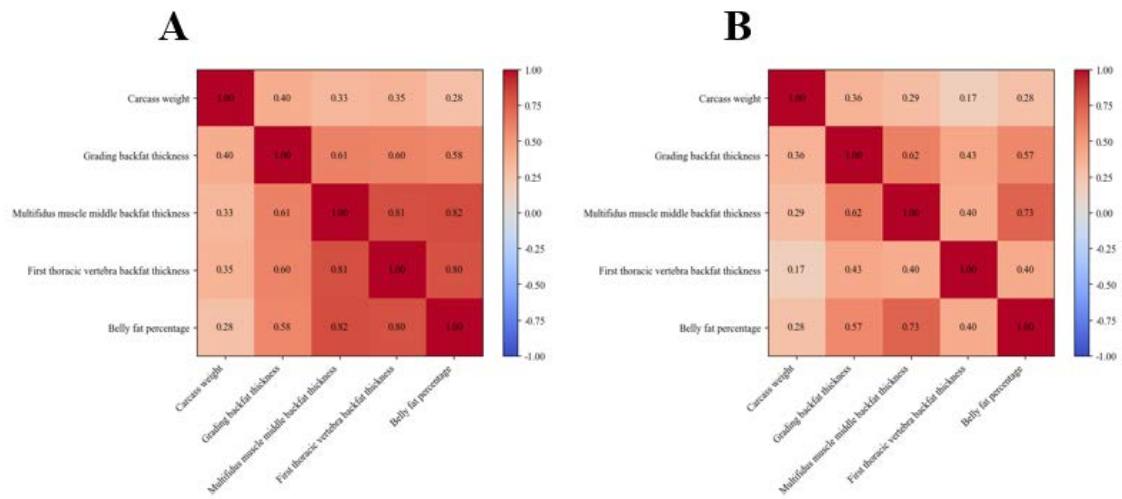


Figure 3. Heatmaps of Pearson's correlation coefficients among carcass weight (CW), grading backfat thickness (GBT), multifidus muscle middle backfat thickness (MBT), backfat thickness at the first thoracic vertebra (FTBT), and VCS2000-derived belly fat percentage (BFP). (A) HC/VCS2000 measurement condition; (B) CC/manual measurement condition. The two panels differ in both carcass state and measurement procedure.

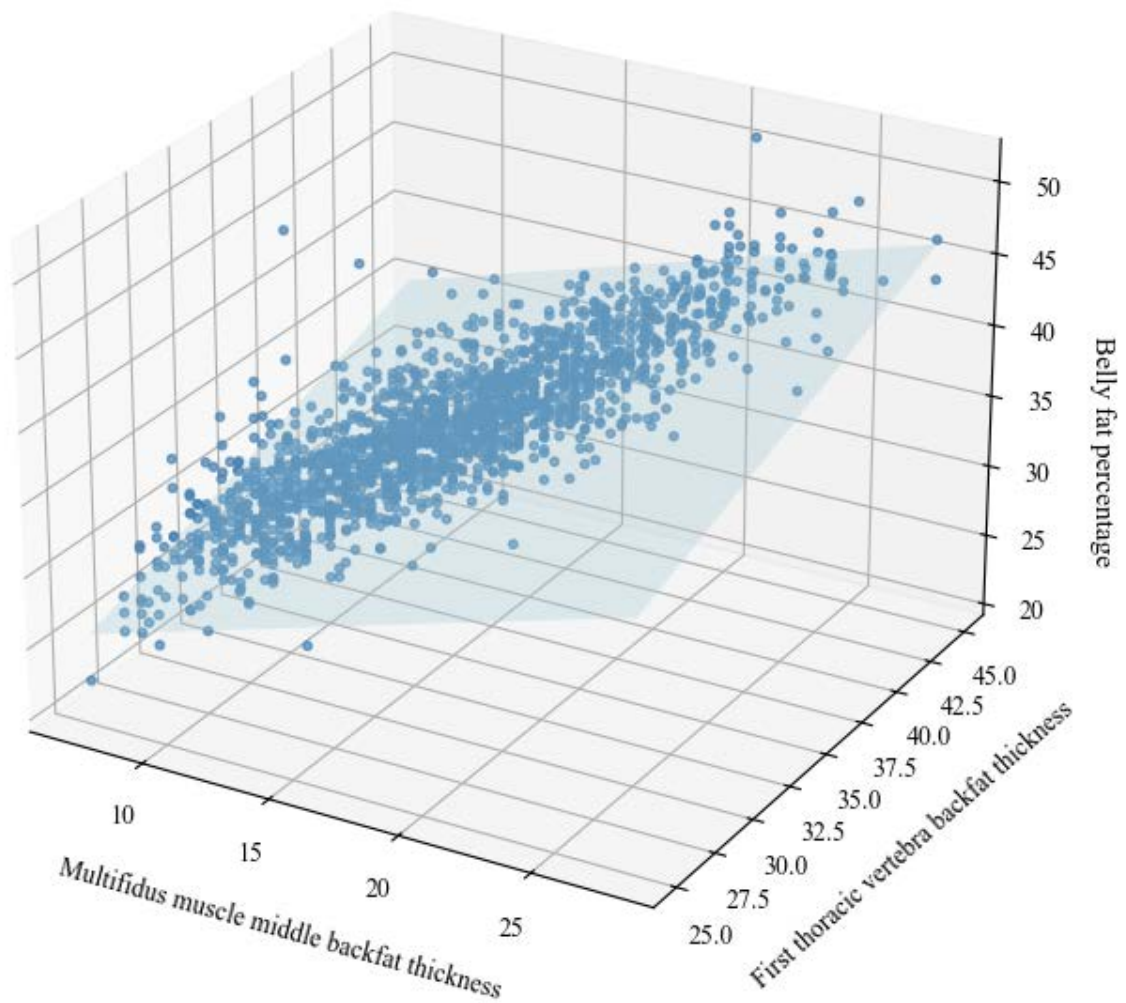


Figure 4. Three-dimensional scatter plot of multifidus muscle middle backfat thickness (MBT), backfat thickness at the first thoracic vertebra (FTBT), and VCS2000-derived belly fat percentage (BFP). The shaded plane represents the fitted post-screening HC two-variable reduced model.

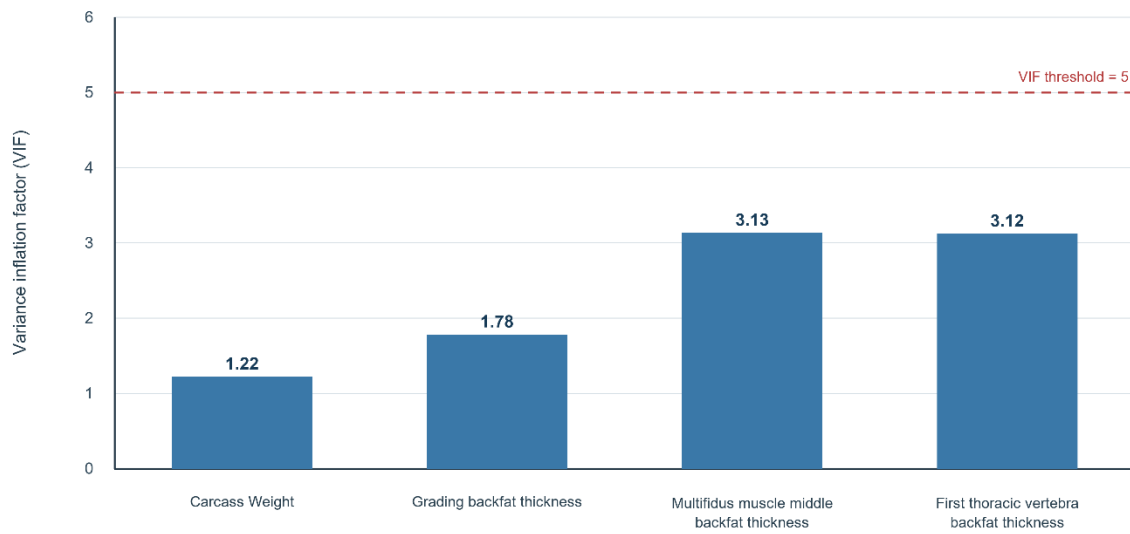
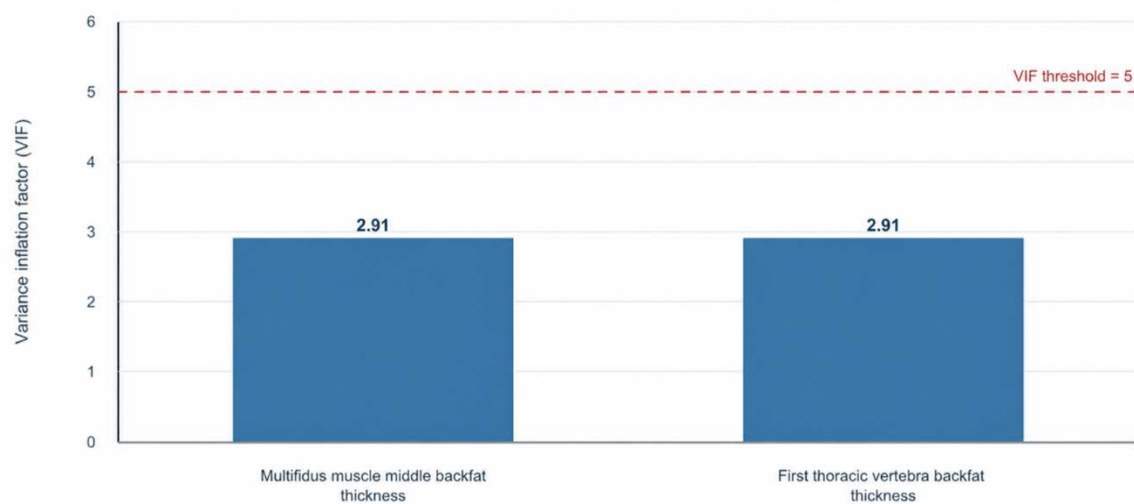
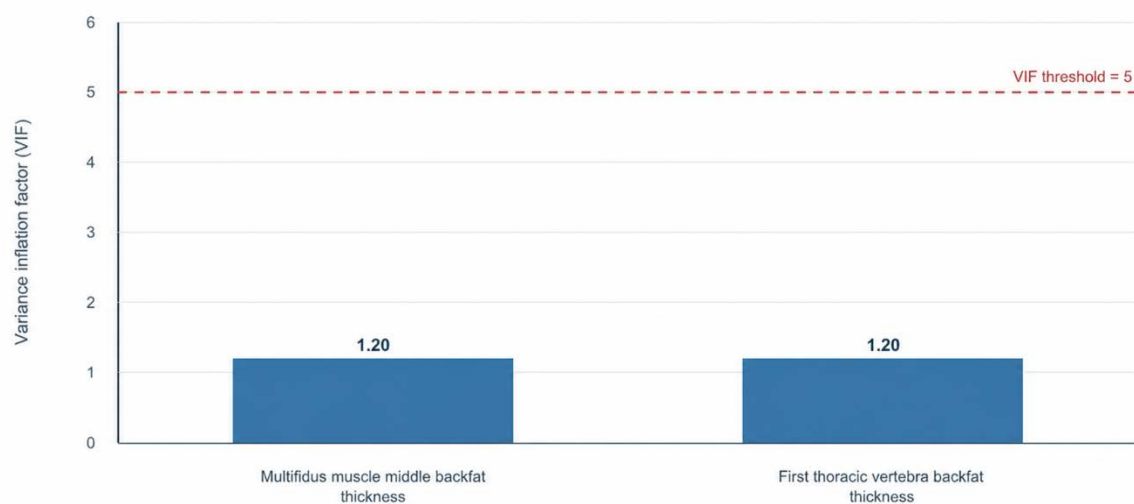


Figure 5. Variance inflation factors (VIFs) for carcass weight (CW), grading backfat thickness (GBT), multifidus muscle middle backfat thickness (MBT), and backfat thickness at the first thoracic vertebra (FTBT) in the HC full benchmark model for VCS2000-derived BFP. VIFs were calculated using the final analytical sample after Cook's distance screening (n = 1,670).



18

19 Figure 6. Variance inflation factors (VIFs) for multifidus muscle middle backfat thickness (MBT) and backfat
20 thickness at the first thoracic vertebra (FTBT) in the HC two-variable reduced model for VCS2000-derived
21 BFP. VIFs were calculated using the final analytical sample after Cook's distance screening (n = 1,664).



22

23 Figure 7. Variance inflation factors (VIFs) for manually measured multifidus muscle middle backfat thickness
 24 (MBT) and backfat thickness at the first thoracic vertebra (FTBT) in the CC/manual two-variable reduced model
 25 for VCS2000-derived BFP. VIFs were calculated using the final analytical sample after Cook's distance
 26 screening (n = 1,653).

27

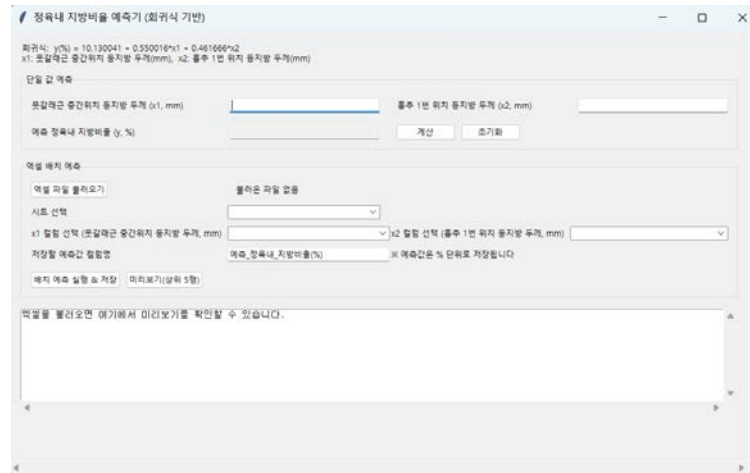


Figure 8. Internal proof-of-concept interface illustrating how the HC two-variable reduced equation could be implemented to estimate VCS2000-derived pork belly fat percentage (BFP) from multifidus muscle middle backfat thickness (MBT) and backfat thickness at the first thoracic vertebra (FTBT). The interface includes single-record entry and optional Excel-based batch processing. Neither the interface nor the underlying candidate equation has been independently or externally validated, and the prototype is not intended for field or commercial decision support.