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Strategies to predict and improve eating quality of cooked beef using carcass and meat composition traits in Angus cattle

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ABSTRACT: Product quality is a high priority for the beef industry because of its importance as a major driver of consumer demand for beef and the ability of the industry to improve it. A 2-prong approach based on implementation of a genetic program to improve eating quality and a system to communicate eating quality and increase the probability that consumers' eating quality expectations are met is outlined. The objectives of this study were 1) to identify the best carcass and meat composition traits to be used in a selection program to improve eating quality and 2) to develop a relatively small number of classes that reflect real and perceptible differences in eating quality that can be communicated to consumers and identify a subset of carcass and meat composition traits with the highest predictive accuracy across all eating quality classes. Carcass traits, meat composition, including Warner-Bratzler shear force (WBSF), intramuscular fat content (IMFC), trained sensory panel scores, and mineral composition traits of 1,666 Angus cattle were used in this study. Three eating quality indexes, EATQ1, EATQ2, and EATQ3, were generated by using different weights for the sensory traits (emphasis on tenderness, flavor, and juiciness, respectively). The best model for predicting eating quality explained 37%, 9%, and 19% of the variability of EATQ1, EATQ2, and EATQ3, and 2 traits, WBSF and IMFC, accounted for most of the variability explained by the best models. EATQ1 combines tenderness, juiciness, and flavor assessed by trained panels with 0.60, 0.15, and 0.25 weights, best describes North American consumers, and has a moderate heritability (0.18 ± 0.06). A selection index (I_s= −0.5[WBSF] + 0.3[IMFC]) based on phenotypic and genetic variances and covariances can be used to improve eating quality as a correlated trait. The 3 indexes (EATQ1, EATQ2, and EATQ3) were used to generate 3 equal (33.3%) low, medium, and high eating quality classes, and linear combinations of traits that best predict class membership were estimated using a predictive discriminant analysis. The best predictive model to classify new observations into low, medium, and high eating quality classes defined by the EATQ1 index included WBSF, IMFC, HCW, and marbling score and resulted in a total error rate of 47.06%, much lower than the 60.74% error rate when the prediction of class membership was based on the USDA grading system. The 2 best predictors were WBSF and IMFC, and they accounted for 97.2% of the variability explained by the best model.

Key words: Angus, beef, eating quality, prediction

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INTRODUCTION

Demand, defined as consumers' ability and desire to buy more beef at a given price and continue to buy it at higher prices, plays a critical role in the economic success of the beef industry (Tonsor and Schulz, 2015). A recent study (Schroeder et al., 2013) identified product quality as a high priority for the beef industry on the basis of its importance as a major driver of consumer demand for beef and the ability of the industry to improve it. The strength shown by the high-quality branded beef market in

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the last few years confirms that a sizable proportion of consumers seeking high quality are willing to pay for assured superior quality. Growing this segment of consumers is important, and meeting eating quality expectations is an appropriate strategy. Even more important for the future of the industry is expanding the consumer base. As the average income increases, new consumers will enter the beef market, and the eating quality they experience will largely determine if they will become habitual beef consumers. Improving quality is therefore critically important for the beef industry to retain and attract consumers. In this study we focus on eating quality, or palatability, and discuss long-term and short-term opportunities for the beef industry to address this attribute as a strategy to increase demand. Improving eating experience when consuming beef and the ability to accurately inform the consumer of the expected eating quality when the product is purchased are critical challenges. The objectives of this study were 1) to identify the best carcass and meat composition traits to be used in a selection program to improve eating quality, 2) to develop a relatively small number of classes that reflect real and perceptible differences in eating quality that can be communicated to consumers, and 3) to identify a subset of carcass and meat composition traits with the highest predictive accuracy across all eating quality classes.

MATERIALS AND METHODS

The Iowa State University and Oklahoma State University Institutional Review Boards approved the experimental protocols used in this study.

Animals and Traits

A total of 1,666 Angus cattle from the Iowa State University (**ISU**) Research Herd and from 2 commercial ranches in California and Oklahoma were used in this study.

Cattle were finished and harvested in 2008 and 2009 at commercial facilities in Iowa (n = 516), California (n = 353), Texas (n = 423), and Colorado (n = 374). Trained personnel obtained carcass measurements, including HCW, rib eye area, marbling score (**MS**), percentage KPH, fat thickness, USDA calculated yield grade (**CALCYG**), and USDA quality grade based primarily on MS. The scale used for data entry of MS was 3.0 = traces, 4.0 = slight, 5.0 = small, 6.0 = modest, 7.0 = moderate, 8.0 = slightly abundant, and 9.0 = moderately abundant.

Sample Collection and Preparation

Carcasses were fabricated according to Institutional Meat Purchasing Specifications (**IMPS**), and sample collection was unique in each plant. Rib sections (IMPS #107) were obtained from each carcass in Iowa, California, and Colorado. In Texas, strip loins (IMPS #180) were collected from each carcass. Samples were collected, vacuum packaged, boxed, and transported to the ISU Meat Laboratory in Ames or the Oklahoma State University (**OSU**) Food and Agricultural Products Center (**FAPC**) in Stillwater for fabrication. Two 1.27-cm steaks were removed for nutrient composition, and external fat and connective tissue were removed. Two 2.54-cm steaks were then removed for Warner-Bratzler shear force (**WBSF**) and sensory analysis. All steaks were vacuum packaged, aged for 14 d from the harvest date at 2°C, and then frozen at −20°C for subsequent analysis. After samples were frozen, WBSF and sensory steaks fabricated in Iowa were transported to the OSU FAPC. Nutrient composition steaks were shipped frozen to the ISU Meat Laboratory for analysis.

Warner Bratzler Shear Force

Frozen steaks were allowed to thaw at 4°C for 24 h before cooking. Steaks were broiled in an impingement oven (XLT Impinger, model 3240-TS, BOFI Inc., Wichita, KS, or Lincoln Impinger, model 1132-000-A, Lincoln Foodservice Products, Fort Wayne, IN) at 200°C to an internal temperature of 68°C. An Atkins AccuTuff 340 thermometer (Atkins Temtec, Gainesville, FL) was used to monitor the temperature of steaks as they exited the oven. If they had not yet reached 68°C, they were returned to the conveyor until they reached 68°C. After cooking, steaks were cooled at 4°C for 18 to 24 h as recommended by the American Meat Science Association (AMSA, 1995). Six cores, 1.27-cm in diameter, were removed parallel to muscle fiber orientation and sheared once, using a Warner-Bratzler head attached to an Instron Universal Testing Machine (model 4502, Instron Corporation, Canton, MS). The Warner-Bratzler head moved at a crosshead speed of 200 mm/min. Peak load (kg) of each core was recorded by an IBM PS2 (model 55 SX) using software provided by the Instron Corporation. Mean peak load (kg) was analyzed for each sample.

Sensory Analysis

Steaks were assigned a randomized number for sensory sessions. Steaks were allowed to thaw at 4°C for 24 h before cooking, cooked to 68°C as described above for WBSF, sliced into approximately 2.54 × 1.27 × 1.27 cm samples, and served warm to panelists.

Sensory attributes of each steak were evaluated by an 8-member, trained panel consisting of OSU personnel. Panelists were trained for tenderness, juiciness, and 3 specific flavor attributes (Cross et al., 1978). Sensory sessions were conducted once or twice per day and contained 12 samples each. Samples were evaluated using a standard ballot from the AMSA (1995). Panelists evaluated samples in duplicate for sustained juiciness (**JUIC**) and overall tenderness (**TEND**) using an 8-point scale. For juiciness, the scale was 1 = extremely dry and 8 = extremely juicy. The scale used for overall tenderness was 1 = extremely tough and 8 = extremely tender. Panelists evaluated cooked beef flavor (**BEEF**), painty/fishy flavor (**FISH**), and livery/metallic flavor (**MET**) intensity using a 3-point scale. The scale used for beef flavor and off-flavor intensity was 1 = not detectable, 2 = slightly detectable, and 3 = strong.

During sessions, panelists were randomly seated in individual booths in a temperature- and light-controlled room. While being served, the panelists were under red filtered lights as suggested by the AMSA (1995). The 12 samples were served in a randomized order according to panelist. The panelists were provided distilled, deionized water and unsalted crackers to cleanse their palate.

Nutrient Phenotype Collection

Nutrient composition samples were frozen and ground before fat, fatty acid, and mineral assays. One 1.27-cm steak was trimmed of external fat and connective tissue and analyzed at ISU (Ames, IA) for nutrient composition, including intramuscular fat content (**IMFC**), determined by ether extraction using method 960.39 of AOAC (2007). An approximately 4-g sample was dried at 105°C for 18 to 20 h (AOAC, 2007). Muscle samples were prepared for mineral analyses using microwave digestion (MDS-2000, CEM, Matthews, NC). Samples were analyzed for their mineral content using inductively coupled plasma–optical emission spectroscopy (SPECTRO Analytical Instruments, Fitchburg, MA) as outlined by AOAC (2007). Concentrations of Ca, Fe, Mg, P, and Zn were calculated.

Statistical Analyses

An observational analytic cohort study was conducted to test the hypotheses of phenotypic and genetic associations of carcass and meat quality traits with eating quality of beef.

Descriptors of Flavor and Eating Quality and Association with Carcass and Composition Traits

An aggregate measure of overall flavor desirability was generated by combining the panel BEEF score as a desirable attribute and the FISH or MET off flavors scores as undesirable. PROC CATMOD of SAS (SAS Inst. Inc., Cary, NC) was used to analyze the association of BEEF class (coded 1 to 7, from low to high intensity) with the number of off flavors detected (coded as 0, 1, or 2). The following equation was used to aggregate these assessments into a single descriptor of flavor desirability (**FLAV**):

$$\text{FLAV} = 2 + (\text{BEEF score}) - (\text{FISH score}) - (\text{MET score}).$$

The sensory attributes TEND, JUIC, and FLAV were standardized with the STDZ procedure of SAS 9.4 using the STD method (location = mean and scale = SD). A general consensus exists that eating quality can be adequately described by 3 sensory attributes; however, it is not clear how to combine these attributes into a single score that could be used as a basis for describing eating quality. In this study an aggregate score was developed using standardized sensory attributes. Three eating quality variables were generated by using different weights for the sensory traits as follows:

$$\text{Eating quality 1 (tender-heavy) EATQ1} = 0.60(\text{TEND}) + 0.15(\text{JUIC}) + 0.25(\text{FLAV}),$$

$$\text{Eating quality 2 (flavor-heavy) EATQ2} = 0.15(\text{TEND}) + 0.25(\text{JUIC}) + 0.60(\text{FLAV}),$$

$$\text{Eating quality 3 (juicy-heavy) EATQ3} = 0.25(\text{TEND}) + 0.60(\text{JUIC}) + 0.15(\text{FLAV}).$$

Forward stepwise regression analysis ($P = 0.05$ for entry and $P = 0.10$ to stay) was used to select from all carcass and composition traits available the best model for predicting eating quality as defined by the EATQ1, EATQ2, and EATQ3 indexes.

Genetic Parameters and Selection Index

The restricted maximum likelihood procedure was used to estimate genetic and residual variances, heritability, and genetic and phenotypic correlations on the basis of 3-trait animal models fitted to the data using WOMBAT (Meyer, 2007) as previously described (Mateescu et al., 2015). Contemporary groups were defined on the basis of gender at harvest (bull, heifer, or steer), finishing location (California, Colorado, Iowa, or Texas), and harvest date for a total of 20 groups. Contemporary groups were fit as fixed effects in all analyses. A pedigree file with 5,907 individuals including identification of all animal, sire, and dam trios for 4 ancestral generations was used to define relationships among animals in the data set. Significance of genetic correlations was obtained as $\theta \pm Z\alpha/2$ (sampling error), assuming normality of the estimator, θ.

An index was created on the basis of best predictors for EATQ1 to be used in a selection program to improve eating quality as a correlated trait. For *N* traits, X1 to XN, an index is created by setting up *N* normal simultaneous equations:

$$b_1\,VP_{(X1)} + b_2\,CovP_{(X1,X2)} + \cdots + b_N\,CovP_{(X1,XN)} = v_1\,VA_{(X1)} + v_2\,CovA_{(X1,X2)} + \ldots + v_N\,CovA_{(X1,XN)},$$

$$b_1\,CovP_{(X1,X2)} + b_2\,VP_{(X2)} + \cdots + b_N\,CovP_{(X2,XN)} = v_1\,CovA_{(X1,X2)} + v_2\,VA_{(X2)} + \ldots + v_N\,CovA_{(X2,XN)},$$

$$\ldots$$

$$b_1\,CovP_{(X1,XN)} + b_2\,CovP_{(X2,XN)} + \cdots + b_N\,VP_{(XN)} = v_1\,CovA_{(X1,X2)} + v_2\,CovA_{(X2,Xn)} + \ldots + v_N\,VA_{(XN)},$$

where VP, CovP, VA, and CovA are phenotypic and genetic variances and covariances for the *N* traits and v_1 to v_N are the weights for the *N* traits. These equations are solved for b_1 to b_N, which are used to create an optimal selection index:

$$I_s = b_1X_1 + b_2X_2 + \cdots + b_NX_n.$$

Predictive Discriminant Analysis

The 3 indexes (EATQ1, EATQ2, and EATQ3) were used to generate 3 equal (33.3%) low, medium, and high eating quality classes. These were labeled EATQ1_Lo, EATQ1_Med, and EATQ1_Hi for the EATQ1 index, with similar labels for the EATQ2 and EATQ3 indexes.

The traits considered in this study are biologically correlated, and a multivariate approach via discriminant analysis was used. Linear combinations of traits that best predict eating quality classes were estimated using a predictive discriminant analysis. The multivariate model used in these analyses was

$$Y_{ijk} = \mu_i + T_{ij} + e_{ijk},$$

where Y_{ijk} is the multivariate vector of observations of trait i for eating quality class j in animal k; μ_i is the multivariate means vector for i traits; T_{ij} is the multivariate vector of effects in eating quality class j on trait i; and e_{ijk} is the multivariate vector for random errors associated with the observations vector Y_{ijk} and has a multinormal distribution.

These linear composites of predictor variables, or classification functions, were used to predict group membership. A cross-validation method was used to estimate the error rate when using the discriminant functions to allocate observations to groups. With this method, 1 observation is held out; the linear classification functions are estimated on the basis of the *n* − 1 remaining observations and used to classify the held-out observation. The process is repeated until all observations have been classified, and the error rates are determined on the basis of the cumulative findings.

Predictive discriminant analyses were performed using only MS, using the best predictors among all carcass traits, and using the best predictors among all carcass and composition traits. The accuracy of prediction was evaluated for each model on the basis of the error rate of classification of new observations into eating quality classes and was used to compare predictability among models and relative to the chance classification error rate using chance classification. Chance error rate (**CER**) for each eating quality index was calculated as follow:

$$CER = 1.0 - (\text{frequency low class})^2 - (\text{frequency medium class})^2 - (\text{frequency high class})^2.$$

To identify a subset of the best predictors (with the lowest error rate) from 6 carcass traits or from all 13 predictors available in the analysis, a stepwise discriminant analysis was used. Specifically, at each step all variables were evaluated, and the variable that contributed the most to the discrimination between groups was identified and included in the model, and the evaluation process was repeated for the remaining variables. At each step, the significance of predictor variables already in the model was evaluated on the basis of the significance for the staying criterion (P = 0.10), and the newly entering variable was evaluated on the basis of the significance for entering (P = 0.05) criterion. The squared canonical correlation measures the proportion of the variance among eating quality groupings explained by predictor variables. The analyses were performed using STEPDIS, DISCRIM, and CATMOD procedures in SAS 9.4.

Table 1. Frequency distribution of beef flavor (BEEF) score of observations with no off flavor detected, with livery/metallic (MET) or painty/fishy (FISH) off flavor detected, and with both off flavors detected

BEEF[1]	No off flavor detected	One off flavor detected	Both off flavors detected	Estimate[2]
BEEF ≤ 2.25	15	141	146	0.435[a]
2.25 < BEEF ≤ 2.375	43	148	97	0.189[a]
2.375 < BEEF ≤ 2.50	98	204	108	0.026[a]
2.50 < BEEF ≤ 2.625	83	190	73	−0.027
2.625 < BEEF ≤ 2.75	63	122	31	−0.147
2.75 < BEEF ≤ 2.875	23	42	11	−0.156[a]
2.875 < BEEF	11	15	2	−0.320[a]
Total	336	862	468	0.998[a]

[a]Estimate significantly ($P < 0.05$) different than zero.

[1]Beef flavor intensity classes were defined on the basis of sensory panel score. The scale used to score BEEF, MET, and FISH intensity was 1 = not detectable, 2 = slightly detectable, and 3 = strong.

[2]Deviation from the mean (0.998 ± 0.02) for the number of off flavors detected for each BEEF class.

RESULTS AND DISCUSSION

Descriptors of Flavor and Eating Quality

Panelists detected none of the off flavors in 336 samples, 1 off flavor (either FISH or MET) in 862 samples, and both off flavors in 468 samples. The frequencies of samples with 0, 1, or 2 off flavors detected and stratified by BEEF score classes are presented in Table 1. The association of beef flavor intensity with number of off flavors was statistically significant ($\chi^2 = 177.7$, $P < 0.0001$). The estimates from the CATMOD analysis and the results of 1 df χ^2 tests for individual parameters are also shown in Table 1. The estimate for the mean (0.998 ± 0.023) is the average number of off flavors detected for the entire population. The expected number of off flavors detected for each BEEF class illustrates the substantial decline in number of off flavors detected with increasing beef flavor intensity (from 1.43 for lowest BEEF class to 0.68 for highest BEEF class).

A series of Australian studies (Thompson et al., 2008; Watson et al., 2008; Polkinghorne and Thompson, 2010) were conducted in association with the development of the Meat Standards Australia (**MSA**) scheme. The eating quality of cooked beef is determined by tenderness, juiciness, and flavor, and the goal in these studies was to develop a function of these sensory traits that best predict eating quality classes as described by a star rating system. A large number of consumers scored samples with respect to tenderness, juiciness, flavor, and overall liking and classified them into 1 of the 4 classes: "unsatisfactory," "good everyday," "better than everyday," and "premium quality," coded as 0, 1, 2, and 3 stars, respectively (Watson et al., 2008). A discriminant analysis was used to develop a linear function of sensory traits that best predicted the star categories of eating quality (Watson et al., 2008). When only tenderness, juiciness, and flavor were used, in line with trained panel scoring, the meat quality linear function (**MQ3**) that best predicted the star categories of eating quality was

$$\mathrm{MQ3} = 0.53(\mathrm{TEND}) + 0.17(\mathrm{JUIC}) + 0.30(\mathrm{FLAV}).$$

In this study the sensory attributes were combined to describe eating quality. Three indexes were generated with different sensory attributes being emphasized. The first index created for this study, EATQ1, places emphasis on tenderness with weights of 0.60 for TEND, 0.15 for JUIC, and 0.25 for FLAV. These weights are in line with many studies identifying tenderness as the most important trait affecting beef eating quality (Dikeman, 1987; Savell et al., 1987; Miller et al., 1995; Savell et al., 1999) and are similar to the weights assigned to these eating quality attributes in the MQ3 index used by MSA (Watson et al., 2008). On the basis of these studies, EATQ1 is considered the most relevant descriptor of eating quality and is the focus of this study, with other indexes considered mostly for comparison reasons.

Several studies have shown that when tenderness reaches an acceptable level, the importance of flavor with respect to beef eating quality increases (Goodson et al., 2002; Killinger et al., 2004; Behrends et al., 2005a,b). Surveys of beef purchasing motivators have also shown the importance of flavor to consumers. In a nationwide survey of U.S. beef consumers, flavor was rated as a very important purchasing motivator for beef steaks and roasts (Reicks et al., 2011). The second eating quality index, EATQ2, places emphasis on flavor, with weights of 0.15 for TEND, 0.25 for JUIC, and 0.60 for FLAV. To cover the entire range, a third eating quality index was also constructed, EATQ3, to emphasize juiciness with weights of 0.25 for TEND, 0.60 for JUIC, and 0.15 for FLAV.

Association of Carcass and Composition Traits with Eating Quality

Mean, SD, and minimum and maximum values for carcass measurements; concentrations of P, Mg, Ca, Fe, and Zn; IMFC; and WBSF from Angus cattle available for this study are presented in Table 2 and are discussed in detail by Mateescu et al. (2013).

The parameter estimates and their SE, t values, and $P > |t|$ for the best models to predict EATQ1, EATQ2, and EATQ3 are shown in Table 3. The best model for EATQ1 has $R^2 = 0.37$, and the first 2 variables, WBSF and IMFC, account for 98% of the variability of EATQ1 explained by the model. The best model for EATQ2 has an $R^2 = 0.09$, indicating that the traits available could explain a much lower proportion of the variability of EATQ2. Although IMFC and WBSF still explain most of the variability of EATQ2, IMFC is the first variable entering the model, and Fe and Mg concentrations are also significant. This suggests that if flavor is emphasized, fat and several minerals play an important role. However, the low predictive power for EATQ2 with the traits available in this study indicates that more objective measures describing flavor need to be identified if flavor becomes an important attribute of eating quality. The recently developed Beef Flavor Lexicon (Adhikari et al., 2011) and the identification of the compounds generated by cooking and responsible for beef flavor (Kerth and Miller, 2015) are important steps toward this goal. The best model for EATQ3 has $R^2 = 0.19$. The IMFC was the first variable entering the model and, together with WBSF, accounts for most of the variation in EATQ3 explained by the best model, suggesting the importance of fat when juiciness is emphasized.

Two important points emerge from this analysis. First, independent of which index is used to define eating quality, the 2 objective measures of tenderness (WBSF and IMFC) are the 2 best predictors and jointly account for most of the variability in eating quality explained by the best predictive models. Second, the EATQ1 index has practical relevance in addressing eating quality because it is based on a substantial amount of consumer research and can be best predicted with available phenotypes.

Genetic Parameters and Selection Index

Heritability, genetic and phenotypic correlations for each eating quality index (EATQ1, EATQ2, and EATQ3), WBSF, and IMFC are shown in Table 4. The EATQ1 index has a moderate heritability (0.18 ± 0.06) that is slightly higher than that of EATQ3 (0.13 ± 0.05), whereas the heritability of EATQ2 is essentially zero (0.04 ± 0.04).

Eating quality as defined by the EATQ1 index is a continuous variable likely to best describe North American consumers. However, because eating quality is difficult and expensive to measure on a large number of individuals, an indirect approach should be considered. Warner-Bratzler shear force and IMFC are objective measures and the best predictors of eating quality, and they should be used to indirectly select for eating quality as a correlated trait. Higher heritability and higher genetic and phenotypic correlations of EATQ1 with predictor traits WBSF and IMFC are additional arguments for using WBSF and IMFC as predictors in a selection program to improve eating quality as defined by the EATQ1 index. A selection index based on these 2 traits was developed using phenotypic and genetic variances and covariances. The weights used for WBSF and IMFC, v_1 and v_2, are their genetic correlations with EATQ1 (−1 and +0.6, respectively). Solving the system of simultaneous equations for b_1 and b_2 resulted in the following selection index:

$$I_S = -0.5(\text{WBSF}) + 0.3(\text{IMFC}).$$

A bivariate animal model of the same data estimated the heritability of the selection index to be 0.42 ± 0.09 and its correlation with the target of selection EATQ1 to be 0.89 ± 0.11, suggesting that a selection program based on this index could be effective in improving eating quality as a correlated trait.

Like many production traits that have an economic value to the beef industry, eating quality can be improved through changes in both management and genetics. The cost of measuring eating quality directly and the fact that a measure on a live breeding candidate is not possible make this trait difficult to improve directly through traditional means. Eating quality is an excellent example of a trait that can be improved via indirect selection using 2 indicator traits genetically corre-

Table 2. Mean, SD, and minimum and maximum values for carcass measurements, including HCW; rib eye area (REA12); marbling score (MS); percentage KPH; fat thickness (FAT12); USDA calculated yield grade (CALCYG); concentrations of P, Mg, Ca, Fe, and Zn; intramuscular fat content (IMFC); and Warner-Bratzler shear force (WBSF) from Angus cattle

Trait	Mean	SD	Minimum	Maximum
HCW, kg	333.01	32.58	222.26	449.05
FAT12, mm	13.46	4.83	3.05	28.45
REA12, cm^2	80.26	7.55	55.49	107.10
KPH, %	2.00	0.35	1.00	3.00
MS[1]	6.04	0.99	3.60	9.20
CALCYG	3.03	0.65	1.14	5.19
P, µg/g meat	2,020.62	286.69	0.82	3,163.15
Mg, µg/g meat	264.95	42.91	156.39	440.74
Ca, µg/g meat	37.02	20.58	3.81	208.65
Fe, µg/g meat	14.48	3.16	5.20	27.43
Zn, µg/g meat	38.36	7.29	22.53	85.68
IMFC, g fat/100 g meat	6.04	2.04	1.41	15.47
WBSF, kg	3.67	0.69	2.12	8.47

[1]The scale used for data entry of MS was 3.0 = traces, 4.0 = slight, 5.0 = small, 6.0 = modest, 7.0 = moderate, 8.0 = slightly abundant, and 9.0 = moderately abundant.

Table 3. The parameter estimates and their SE, t values, and $P > |t|$ for the best models to predict EATQ1, EATQ2, and EATQ3 using forward stepwise regression analysis[1]

Eating index	Parameter[2]	Estimate	SE	t Value	$P > \|t\|$	PR-Sq	F	$P > F$
EATQ1	Intercept	2.00	0.18	11.08	<0.0001			
	WBSF	−0.52	0.02	−25.08	<0.0001	0.34	837.5	<0.00001
	IMFC	0.08	0.01	7.58	<0.0001	0.03	80.2	<0.0001
	MS	−0.06	0.02	−2.97	0.003	0.004	9.5	0.002
	FAT12	0.27	0.08	3.27	0.001	0.003	7.4	0.007
	HCW	−0.0005	0.0002	−2.52	0.012	0.002	6.3	0.012
EATQ2	Intercept	0.49	0.18	2.67	0.008			
	IMFC	0.07	0.01	6.29	<0.0001	0.05	89.5	<0.0001
	WBSF	−0.14	0.02	−6.15	<0.0001	0.02	32.5	<0.0001
	MS	−0.08	0.02	−3.71	00.0002	0.007	13.4	0.0003
	FAT12	0.24	0.09	2.70	0.007	0.004	6.5	0.011
	Fe	0.02	0.01	3.13	0.0018	0.002	4.0	0.045
	Mg	−0.001	0.0004	−2.59	0.0098	0.004	6.7	0.010
EATQ3	Intercept	0.02	0.13	0.18	0.857			
	IMFC	0.10	0.01	12.55	<0.0001	0.15	281.4	<0.0001
	WBSF	−0.23	0.02	−9.66	<0.0001	0.05	91.7	<0.0001
	Fe	0.01	0.01	2.67	0.0077	0.003	7.1	0.008

[1] $P = 0.05$ for entry, and $P = 0.10$ to stay. Partial R^2 (PR-Sq), F value (F), and $P > F$ for each trait selected for inclusion are shown.

[2] IMFC = intramuscular fat content; WBSF = Warner-Bratzler shear force; MS = marbling score.

lated with the target trait. However, the indicator traits, WBSF and IMFC, are impossible or difficult to measure on live animals. A DNA test that can accurately identify cattle with superior genetics for WBSF and IMFC would help to overcome these challenges. The application of genomics in beef cattle breeding is progressing. For several beef breeds, breeding values for tenderness and marbling incorporating genomic information are already available, suggesting that genomic predictions for eating quality combining WBSF and IMFC in an optimal index to select for eating quality is also feasible. The lacking incentive to promote development and adoption of such a program is a clear market signal to producers regarding the economic importance of eating quality for the competitiveness of beef industry. An eating quality assurance program would provide the needed incentives and encourage industry stakeholders, cow-calf producers in particular, to invest in a genomic selection program to improve eating quality. The implementation of a tenderness verification program (USDA Agricultural Marketing Service, 2012) is certainly a positive step toward this goal.

Prediction of Eating Quality with Carcass and Composition Traits

The quality index is a continuous variable that could be used in a selection program. However, to communicate eating quality to consumers, a reduced number of categories, or classes that can be used as labels, is needed. The second objective was to assess the accuracy of predicting eating quality classes defined by 3 indexes using carcass and meat composition traits and to identify a subset of traits with the highest predictive accuracy across all eating quality classes.

Table 4. Estimates of heritability (diagonal) and genetic (above the diagonal) and phenotypic (below the diagonal) correlations with approximate SE (in parentheses) for each eating quality index, Warner-Bratzler shear force (WBSF), and intramuscular fat content (IMFC) of steaks from Angus cattle[1]

Item	EATQ1	EATQ2	EATQ3	WBSF, kg	IMFC, g
EATQ1	0.18 (0.06)			−0.99 (0.09)	0.62 (0.17)
EATQ2		0.04 (0.04)		−0.99 (0.55)	0.35 (0.44)
EATQ3			0.13 (0.05)	−0.76 (0.17)	0.95 (0.15)
WBSF, kg	−0.49 (0.02)	−0.17 (0.03)	−0.29 (0.02)	0.25 (0.07)	−0.50 (0.15)
IMFC, g	0.22 (0.03)	0.09 (0.03)	0.29 (0.02)	−0.24 (0.03)	0.45 (0.10)

[1] Three eating quality variables were generated by using different weights for the sensory traits: EATQ1 = 0.60(TEND) + 0.15(JUIC) + 0.25(FLAV) (or tender-heavy); EATQ2 = 0.15(TEND) + 0.25(JUIC) + 0.60(FLAV) (or flavor-heavy); EATQ3 = 0.25(TEND) + 0.60(JUIC) + 0.15(FLAV) (or juicy-heavy), where TEND = overall tenderness, JUIC = sustained juiciness, and FLAV = flavor desirability.

Table 5. Frequency distribution of USDA quality grade by EATQ1[1]

	USDA quality grade						
EATQ1	Select	Choice-	Choice	Choice+	Prime-	Prime	Total
EAT1_Lo	5	99	279	124	27	21	555
Row percentage	0.90%	17.84%	50.27%	22.34%	4.86%	3.78%	100%
Column percentage	35.71%	50.77%	36.81%	27.56%	18.24%	20.79%	33.31%
EAT1_Med	5	47	273	160	48	23	556
Row percentage	0.90%	8.45%	49.10%	28.78%	8.63%	4.14%	100%
Column percentage	35.71%	24.10%	36.02%	35.56%	32.43%	22.77%	33.37%
EAT1_Hi	4	49	206	166	73	57	555
Row percentage	0.72%	8.83%	37.12%	29.91	13.15%	10.27	100%
Column percentage	28.57%	24.62%	26.91%	36.67%	49.32%	56.44%	33.31%
Total	14	195	758	450	148	101	1,666
Row percentage	0.84%	11.70%	45.50%	27.01	8.88%	6.06%	100%
Column percentage	100%	100%	100%	100%	100%	100%	100%

[1]EATQ1 is an eating quality class constructed using a linear function of tenderness, juiciness, and flavor and divided into 3 equal classes: low (EAT1_Lo), medium (EAT1_Med), and high (EAT1_Hi).

Our data consisted of Angus cattle less than 42 mo of age at slaughter; therefore, the degree of marbling was the primary determinant of quality grade. Using the USDA grading system, 0.82% of carcasses graded as Select, 11.66% as Choice-, 45.41% as Choice, 26.91% as Choice+, 9.01% as Prime-, and 6.18% as Prime. The distributions of observations in each USDA quality grade with respect to low, medium, and high eating quality classes based on EATQ1 index are shown in Table 5. A χ^2 test indicates a statistically significant difference between the underlying distributions of eating quality classes and USDA quality grades ($\chi^2 = 92.58$, $P < 0.0001$). The data in Table 5 show that the probability of having a positive eating experience increases with quality grade and vice versa for the probability of having a negative eating experience. Proportions of carcasses graded Choice-, Choice, Choice+, Prime-, and Prime in the high eating quality group increase from 24.62% to 56.44%, and those in the low eating quality group decrease from 48.21% to 18.81%. This means that for this data set and with eating quality classes defined by EATQ1 index, if a consumer purchases Choice- beef, the probability of a high-quality eating experience is practically 1 in 4, whereas the probability of a low-quality eating experience is 1 in 2. The probability of a high-quality eating experience for a consumer purchasing Prime beef is 1 in 2, whereas the probability of a low-quality eating experience is 1 in 5. The data presented in Table 5 suggest that there is a desirable but weak association between quality grade and eating quality and predicting eating quality on the basis of quality grades is not very reliable. These results are in agreement with previous studies designed to quantify the contribution of marbling to differences in eating quality of beef that also conveyed low to moderate positive relationships between marbling and cooked beef tenderness, juiciness, and flavor (Jeremiah et al., 1970, Smith et al., 1985). Beef is a relatively expensive protein source, and "taste," or palatability, is an important attribute influencing a consumer's decision to purchase beef over other animal protein sources. In this context, misclassification when using the USDA grading system to predict eating quality is important and could have significant negative consequences on demand for beef.

The results from the predictive discriminant analysis evaluating the usefulness of other carcass and meat quality and composition traits in predicting low (EAT1_Lo), medium (EAT1_Med), and high (EAT1_Hi) eating quality classes defined on the basis of the EATQ1 index are shown in Table 6.

When the prediction of eating quality class membership was based on only MS (model 1), the error rates of classification of new observations into low, medium, and high eating quality classes were 39.82%, 94.24%, and 48.11% for a total error rate of 60.74%, only slightly better than using chance classification, CER of 66.66%. The best predictive model based only on carcass traits included MS, CALCYG, and HCW (model 2). With this model, the error rates of classification of new observations into low, medium, and high eating quality classes were 46.85%, 81.29%, and 48.65% for a total error rate of 58.94%, indicating only a modest improvement in predicting eating quality classes relative to chance classification or the current practice based on MS. The best predictive model when all carcass and composition traits were considered included WBSF, IMFC, HCW, and MS (model 3) and resulted in error rates of classification of new observations into low, medium, and high eating quality classes of 42.70%, 59.35%, and 39.10%, respectively, for a total error rate of 47.06%.

Table 6. Cross-validation classification summary for low (EAT1_Lo), medium (EAT1_Med), and high (EAT1_Hi) eating quality classes defined on the basis of the EATQ1 index[1]

Model	Class	EAT1_Lo No.	EAT1_Lo %	EAT1_Med No.	EAT1_Med %	EAT1_Hi No.	EAT1_Hi %	Total No.	Total %	Error rate, %
Model 1	EAT1_Lo	334	60.18	301	54.14	237	42.7	872	52.34	39.82
	EAT1_Med	58	10.45	32	5.76	30	5.41	120	7.20	94.24
	EAT1_Hi	163	29.37	223	40.11	288	51.89	674	40.46	48.11
	Total	555	100	556	100	555	100	1666	100	60.74
Model 2	EAT1_Lo	295	53.15	240	43.17	183	32.97	718	43.1	46.85
	EAT1_Med	92	16.58	104	18.71	87	15.68	283	16.99	81.29
	EAT1_Hi	168	30.27	212	38.13	285	51.35	665	39.92	48.65
	Total	555	100	556	100	555	100	1666	100	58.94
Model 3	EAT1_Lo	318	57.30	152	27.34	54	9.73	524	31.45	42.70
	EAT1_Med	154	27.75	226	40.65	163	29.37	543	32.59	59.35
	EAT1_Hi	83	14.95	178	32.01	338	60.90	599	35.95	39.10
	Total	555	100	556	100	555	100	1666	100	47.06

[1]Number and percentage of observations classified into EAT1_Lo, EAT1_Med, and EAT1_Hi categories are based on marbling score (model 1), the best carcass traits model (model 2 with MS, USDA calculated yield grade, and HCW), and the best of all traits model (model 3 with Warner-Bratzler shear force, intramuscular fat content, HCW, and marbling score).

The effects of model used in prediction ($\chi^2 = 82.31$, $P < 0.0001$) and of EATQ1 class ($\chi^2 = 714.56$, $P < 0.0001$) on prediction error rates (coded 0 or 1) were statistically significant. The estimates and their SE from 1 df contrasts comparing the effect of 3 models and 3 eating quality classes on prediction errors are shown in Table 7. The decrease in error rate for model 3 (-0.20 ± 0.02 and -0.12 ± 0.02) was statistically significant ($P < 0.0001$) relative to model 1 and model 2 (Table 6), but the decrease in error rate using model 2 was not statistically significant ($P = 0.25$) relative to model 1. The results in Tables 6 and 7 indicate a significant improvement in predicting EATQ1 classes when using WBSF, IMFC, HCW, and MS as predictors (model 3) with a 29% reduction of total error rate relative to the current system based on MS (model 1). Also, the reduction in prediction error rate when using the best carcass traits (model 2) is minimal and not statistically significant relative to the prevailing system (model 1).

All models performed poorly when classifying observations in the EAT1_Med class, which is expected, given that errors could occur in both directions for the middle class. The estimated error rate difference in the probability of classification errors predicting observations in the EAT1_Med class relative to the average error rate predicting observations in the EAT1_Lo and EAT1_Hi classes was 0.34 ± 0.01, significantly ($P < 0.0001$) greater than zero (Table 7). With all models, the misclassification error rates were similar for EAT1_Lo and EAT1_Hi classes (-0.02 ± 0.02), and the difference was not statistically significant ($P = 0.21$; Table 7).

Although no errors are desirable, from the consumer and marketing point of view errors may have different consequences. We could speculate that misclassification errors for the EAT1_Med class have relatively small market consequences. If we assume that the price of the product reflects eating quality, the consumer is paying and expecting average eating quality, and this expectation is most likely met. On the other hand, misclassifications of a product with low or high eating quality may have a greater negative impact on consumers. Again, if we assume the eating quality is positively associated with the price of the product, not meeting quality expectations leads to dissatisfied consumers. This would be similar to the experience of 25% of consumers who paid a higher price to purchase Choice+ or a higher grade beef having a negative eating experience when consuming it (Table 5). This could have important consequences because past experience is a critical factor regarding attitude toward food. A report (SMART, 1994) evaluating the factors contributing to the intent of consumers to repurchase a product concluded that eating quality was the most important factor (65%), followed by price (28%). Unfulfilled eating quality expectations lead to consumers' dissatisfaction, reduced future beef purchases, and lower demand. The negative consequences associated with misclassifications of carcasses with high eating quality into medium or low groups are of different nature. These errors represent opportunity losses for the industry as the product is undervalued (27% of carcasses graded Choice or lower had a high eating quality; Table 5).

The same approach was used to identify the best predictive model for low, medium, and high eating quality classes defined on the basis of the EATQ2 index with emphasis on flavor or the EATQ3 index with emphasis on juiciness. Traits included in the best pre-

Table 7. Orthogonal contrasts comparing the effect of 3 predictive models and 3 eating quality classes based on the EATQ1 index on prediction error rate[1]

Contrast	Estimate	χ^2	DF	$P > \chi^2$
MODEL: Model 3 vs. Model 1	−0.20 ± 0.03	64.39	1	<0.0001
MODEL: Model 3 vs. Model 2	−0.12 ± 0.02	51.29	1	<0.0001
MODEL: Model 2 vs. Model 1	−0.02 ± 0.02	1.35	1	0.246
EATQ1: EAT1_Lo vs. EAT1_Hi	−0.02 ± 0.02	1.59	1	0.208
EATQ1: EAT1_Med vs. [(EAT1_Lo+EAT1_Hi)/2]	0.34 ± 0.01	712.84	1	<0.0001

[1]Model 1 included only marbling score (MS); model 2 (best carcass traits) included MS, USDA calculated yield grade, and HCW; and model 3 (best of all traits) included Warner-Bratzler shear force, intramuscular fat content, HCW, and MS. EAT1_Lo, EAT1_Med, and EAT1_Hi are low, medium, and high 33.3% classes. EATQ1 = 0.60(TEND) + 0.15(JUIC) + 0.25(FLAV) (or tender-heavy), where TEND = overall tenderness, JUIC = sustained juiciness, and FLAV = flavor desirability.

Table 8. Traits selected using forward stepwise discriminant analysis (P = 0.05) to predict class membership with low, medium, and high eating quality classes defined on the basis of the EATQ1, EATQ2, and EATQ3 indexes[1]

Eating index	Trait[2]	R-Sq	F	$P > F$	SCC
EATQ1	WBSF	0.24	265.2	0.0001	0.12
	IMFC	0.04	36.5	0.0001	0.14
	HCW	0.004	3.6	0.028	0.14
	MS	0.004	3.4	0.033	0.14
EATQ2	WBSF	0.06	50.3	0.0001	0.03
	IMFC	0.01	9.9	0.0001	0.03
	Fe	0.006	5.2	0.006	0.04
	MS	0.006	4.9	0.006	0.04
	Ca	0.004	3.1	0.004	0.04
EATQ3	IMFC	0.12	118.1	0.0001	0.06
	WBSF	0.04	34.5	0.0001	0.08
	Fe	0.004	3.6	0.0001	0.08

[1]Partial R^2 (R-Sq), F value (F), and $P > F$ for each trait selected for inclusion and squared canonical correlation (SCC) for each sequential predictive model are shown.

[2]WBSF = Warner-Bratzler shear force; IMFC = intramuscular fat content; MS = marbling score.

dictive model for classes based on EATQ1, EATQ2, and EATQ3, the partial R^2, the F value and $P > F$, and the average squared canonical correlation for each sequential model are shown in Table 8. With the traits available in this study, the ability to predict eating quality classes was 57% on the basis of EATQ3 and 29.6% on the basis of the EATQ2 index, much lower relative to predicting classes based on the EATQ1 index. Also, the model to predict EATQ2 classes included Fe and Ca content, but the predictive ability of the model was rather low, indicating that if flavor is important, other traits are needed to improve prediction.

Independent of how eating quality is defined, WBSF and IMFC are the best 2 predictors. The contribution of WBSF and IMFC to the predictive model for eating quality classes based on the EATQ1, EATQ2, and EATQ3 indexes described by the average squared canonical correlations shown in Table 5 was 13.8%, 8.0%, and 3.4%, respectively.

Implications for Industry

The challenge for the industry with respect to eating quality is complex, and a systems approach that encompasses pre- and postharvest production practices, meat science, and genetics is needed. Consumers are the last link of the beef production chain, and delivering a consistent eating quality is critically important in building consumers' confidence and loyalty and, subsequently, increasing the demand for beef. Currently, emphasis is on postmortem aging, reported to be an average aging time of 20.5 d at retail (Guelker et al., 2013), and increased marbling. However, increasing marbling and aging of product to obtain beef with adequate eating quality are costly, and additional strategies that could deliver superior eating quality and lower cost should be developed. To address this issue, a 2-prong approach aimed at improving eating quality and consumers' satisfaction should be used.

The first step is implementation of a genetic program to permanently and cumulatively improve eating quality. Such a program would deliver superior eating quality with less marbling and shorter aging time and would also increase the value of the carcass by increasing the number of cuts with superior eating quality. In this study, eating quality defined by EATQ1 is considered a relevant breeding objective, and a selection index based on 2 indicator traits, WBSF and IMFC, was developed to select for eating quality as a correlated trait in Angus cattle. The indicator traits are difficult to measure on live animals, and a DNA test that can accurately identify cattle with superior genetics for WBSF and IMFC would help to overcome this difficulty.

The second and equally important step is the development and implementation of a system to communicate eating quality to consumers and improve the probability that consumers' eating quality expectations are met. An appropriate strategy should be the development of a relatively small number of classes that reflect real and perceptible differences in eating quality that can be communicated to consumers using a simple system, such as labeling. In this study the EATQ1 index was used to define 3 equal classes defining low, medium, and high eating quality. A predictive model that would assign the product (whole carcasses or components) to the appropriate eating quality class on the basis of WBSF and IMFC indicators was developed and was shown to be significantly better in predicting eating quality relative to the current system based on USDA quality grade. The drawback is the lengthy and expensive process required to measure these indicator traits. The development of instrument-based objective alternative measures that could be performed on uncooked meat without slowing down production in the processing plant would greatly facilitate the development and implementation of a palatability assurance program. This would increase significantly the consumers' ability to purchase a product with consistent and expected eating quality and value.

The MSA system stands out as an industry model for implementation of an eating quality assurance program (Polkinghorne et al., 2008) that uses a quality management approach to predict beef palatability on the basis of animal traits and technological factors. A recent study (Griffith and Thompson, 2012) estimated the cumulative gross benefits for the Australian beef industry of the MSA program to be $523 million for retail, $430 million for wholesale, and nearly $250 million for producers. These gross benefits are in Australian dollars and are derived for a voluntary system implemented in a country with significantly fewer cattle than the United States, indicating that implementation of an eating quality assurance program is likely to be economically beneficial.

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