APPLICATION OF PARTIAL LEAST SQUARES REGRESSION TO PREDICT DRY MATTER INTAKE AND FEED EFFICIENCY BASED ON FEEDING BEHAVIOR PATTERNS IN BEEF CATTLE

A Thesis

by

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ABSTRACT

Feed expenses are the largest driver of input cost in the beef industry, thus, increasing the genetic merit of beef cattle efficiency is an effective strategy to improve the environmental and economic sustainability of beef production. Residual feed intake (**RFI**) is a measure of feed efficiency independent of average daily gain **(ADG**) and body weight (**BW**), whereby feed-efficient animals consume less feed than expected. Numerous studies have documented that cattle with divergent RFI phenotypes have distinctly different feeding behavior (**FB**) patterns, demonstrating their potential as bio-markers to predict feed efficiency. The nexus of this research lies in the development of animal behavior tracking systems and understanding the relationships between FB patterns and RFI. The first objective of this research was to validate a high-frequency RFID system to quantify frequency and duration of bunk visit (**BV**) events in beef cattle. The accuracy of the system to measure these traits was determined to be 81 and 90% accuracy, respectively. The second objective was to develop predictive equations for feed efficiency traits using FB traits as independent variables. Because FB traits are highly correlated, partial least squares (**PLS**) regression was used in this study as this method is better suited to deal with collinearity among independent variables. This study was conducted using data collected from composite Angus steers (N = 508; Initial BW 309 ± 56 kg) fed a high-grain diet in pens equipped with electronic feed bunks (GrowSafe® Systems). Individual dry matter intake (**DMI**), FB traits, and 14-d BW were measured for 70-d, and RFI calculated as the residual from the regression of DMI on ADG and $BW^{0.75}$. Cattle were ranked by RFI and assigned to 1 of 3 RFI classes based on ± 0.5 SD from the mean RFI. For each animal, 17 FB traits were evaluated: frequency and duration of bunk visit and meal events, head-down

(**HD**) duration, time-to-bunk (**TTB**) interval, maximum non-feeding interval, and corresponding day-to-day variation (**SD**) of these traits. Additionally, 3 ratio traits were considered: BV frequency per meal event, HD duration per meal event and HD duration per BV event. Data analysis was conducted using a mixed-model (SAS 9.4) that included fixed effects of RFI class, trial and pen within trial. Feed-efficient steers consumed 16% less feed, while ADG and BW did not differ from high-RFI animals. Compared to high-RFI steers, low-RFI steers had 18% fewer and 24% shorter BV events and 11% fewer meal events that that were 13% shorter ($P < 0.01$) in length. Feed efficient steers exhibited 10% less ($P < 0.05$) day-to-day variation in DMI, as well as 11 to 33% less ($P < 0.05$) day-to-day variance in frequency and duration of BV and meal events. Furthermore, low-RFI steers had 9% longer ($P < 0.05$) TTB,and 7% greater ($P < 0.05$) day-to-day variation in TTB compared to high-RFI steers. Partial least squares analysis identified 9 FB traits that explained 42% of the inter-animal variation in RFI. These results demonstrate that feed-efficient animals spend less time eating, visit the bunk less frequently for less total time per day and have more consistent day-to-day FB patterns compared to less-efficient animals. Further, these results indicate that FB traits may be useful as bio-marker to identify cattle that are more biologically efficient.

DEDICATION

To Mom and Dad,

Who taught me to follow Jesus Christ as my Savior,
Work Hard,
Live to Learn,
And Love Cattle.

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The analysis depicted in Chapter II was collected in collaboration with ABGI Tag and Traq, of Greenville TX. Data from Chapter III was composited from 3 trials conducted from 2008-2010 by PI Gordon Carstens with cattle provided by the Rex Ranch, Ashby Nebraska at the AgriLife Research Station in McGregor Texas.

All work conducted for the thesis was completed by the student independently.

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NOMENCLATURE

ADG	average daily gain
BCS	body condition score
BW	body weight
$BW^{0.75}$	metabolic body weight
BV	bunk visit
DM	dry matter
DMI	dry matter intake
Duration	length of event
FB	feeding behavior
FCR	feed conversion ratio
G:F	gain-to-feed ratio
GLM	general linear model
LM	longissimus muscle
HD	head down
RG	residual gain
RFI	residual feed intake
SD	standard deviation
SE	standard error
s	second
d	day

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CHAPTER I

INTRODUCTION AND LITERATURE REVIEW

A well-known and often quoted fact in the agriculture industry is the predicted explosion in human population within the next 30 years, with an expected 10 billion people inhabiting the planet by the year 2050 (Capper, 2011). The FAO, (2009) suggests that food production will have to increase by 70% over current levels to fulfill the nutrient and caloric demands associated with this type of population increase. However, livestock producers face fierce competition for a finite resource base of agricultural land, energy, and water which will only increase as the population grows and urban encroachment continues in rural areas. The need to meet society's needs without compromising the ability of future generations to meet their own needs is critical as scientists work to develop new technology designed to increase environmental responsibility in an economically viable and socially acceptable manner.

It is no secret that feed inputs comprise the greatest portion of the annual cost of beef production. To increase the profitability of the cattle industry, feed inputs costs must be reduced without significantly impacting the current level of production. Comparison of historical production from the year 1977 with 2007 indicates that the average beef cattle slaughter weight has increased from 274 to 351 kg, while growth has accelerated from 0.71 to 1.16 kg/d (Capper et al., 2012). Increased growth has reduced animal age at slaughter from 608 to 485-d, resulting in an 8% reduction in energy expended for maintenance (Capper et al., 2012). However, unlike the poultry and swine industry which has decreased the actual energy required for animal maintenance, the beef industry's reduction in total energy apportioned to maintenance is the result of increased growth rates and heavier harvest weights, not an actual decrease in the maintenance energy requirement (Carstens, 2006). This highlights an underlying need to select animals for efficiency of energy used for maintenance, independent of production traits. Thus, the identification and selection of animals with a favorable feed efficiency will allow the beef industry to continue the current trend of reducing the use of resources with minimal impact on production.

Feed Efficiency and Feed Intake

A complex series of independent mechanisms drive energy intake. This has led to at least two distinct theories yielding multiple models seeking to accurately predict feed intake in ruminants (Allen, 2014). Since the animals gastro-intestinal tract composes a constant percentage of the animal's body weight (Demment and Soest, 1985) and the animals metabolism follows a fractional power of its body weight (Kleiber, 1947), it is obvious that the two systems interact in a concurrent manner with each other, making a model predicting feed intake difficult to derive. Physical limitations such as gastrointestinal fill, environmental temperature, and availability and physical nature of the feed stuff (Landers et al., 1967) are successful when predicting intake in poor quality, fibrous feedstuffs, but experience limited success with energy dense feeds. Metabolic limitations include integrity of the hypothalamic structures, emotional and conditional response, metabolites, hormones as well as the age and condition of the animal (Allen, 2014; NRC, 2000; NASEM, 2016). The unexplained variation in predicted vs. actual feed intake is indicative of differences in net feed efficiency, or the total amount of feed required for the maintenance and production of product from any singular individual (Meyer et al., 2008). This allows for selection of animals expressing a certain combination of a multitude of traits which allow them to be more efficient, thus allowing for a decrease in feed inputs.

Feed Conversion Ratios

In meat animals, particularly those destined for the meat supply chain, gross efficiency ratios such as F:G (pounds of feed per pound of gain) and G:F (pound of gain per pound of feed) provide a simple and practical means of expressing efficiency that makes sense in the feedlot production scenario. The use of ratios continues into the meat sector, where gain can be defined as the total carcass gain or the total gain in lean muscle tissue (Archer A.D. et al., 1999). Brelin and Brannang, (1982) summarized 4 studies, indicating a strong (0.61 to 0.95) genetic correlation between growth rate and feed to gain ratio, leading some scientists to conclude that there is minimal need to measure intake since growth is a highly correlated trait indicative of overall efficiency during the feeding and growth phase of the animal (Korver, 1988; Mrode et al., 1990). Performance ratios are not truly comparative across groups, due to breed type variations, sex, and composition of gain. Previous plane of nutrition also becomes an important consideration when compensatory gain becomes a factor. Elimination of certain extraneous influence is possible by feeding all animals for a pre-specified period, or by feeding to a certain metabolic endpoint. However, all fail to meet the biological needs across various breeds and management systems (Archer A.D. et al., 1999).

Feed efficiency in growing animals has been extensively described, primarily utilizing Feed Conversion Ratio (FCR) in feedlot situations where it is easily measured (Bishop et al., 1991; Arthur et al., 2001a). While FCR is shown to be a highly heritable trait easily measured in the feedlot, a strong correlation between FCR and increased mature size threatens the efficacy of this measurement as a selection tool for breeding stock (Archer A.D. et al., 1999; Crews et al., 2005; Nkrumah et al., 2007b). The unintended increase in mature body size drastically increases cowherd maintenance requirements. Since the cowherd is responsible for much of the maintenance requirement of the beef production system (Miller et al., 2001; Capper, 2012), this results in a net negative movement from the intended purpose of increasing overall efficiency of resource utilization. Feed conversion ratios do not partition energy between maintenance and growth (Carstens, 2006), and improvement of FCR may not improve efficiency of production. Thus, the need for another metric to accurately segregate energy into proper partitions is required to accurately select animals with decreased maintenance requirements.

Residual Feed Intake

Residual feed intake (RFI), also known as net feed intake, gained popularity in recent years as a means of identifying animals excelling in genetic traits which serve to make an animal more feed efficient (Moore et al., 2009). Originally proposed by Koch et al., (1963), residual feed intake selects animals for traits independent of measured production outputs (Herd and Arthur, 2009). Feed intake is partitioned into two components, predicted feed intake based on production and a residual, or deviation from the predicted (Herd et al., 2003). Koch realized application of his selection concept required the ability to measure feed intake of every animal in the industry at large. Over thirty years later, technology caught up with his underlying idea and the economical collection of feed intake data became a reality.

Residual feed intake divides feed intake into two components, the predicted intake based upon an animal's metabolic body weight, production variables, and the residual portion describing the deviation from actual versus predicted (Kennedy et al., 1993; Herd et al., 2003). Feed efficient animals exhibit lower or negative residuals while less efficient animal are identified by positive or higher residuals or consumed more feed than necessary for given production. This method of correcting feed intake for body size and production outputs yields an economically relevant index (Gibson and Kennedy, 1990) independent of component traits, helping mitigate indirect selection for growth and increased mature size or productivity (Archer A.D. et al., 1999; Basarab et al., 2003; Lancaster et al., 2009b). RFI seeks to reduce total feed consumption without putting negative emphasis on economically important traits in the offspring, making it extremely applicable to the cow-calf sector (Arthur et al., 2004). Additionally, RFI is shown to be moderately heritable (0.35 to 0.45) (Arthur et al., 2001b; Schenkel et al., 2004; Lancaster et al., 2009b), indicating a potential for efficiency improvement via genetic selection. But given the numerous sources of variation within residual feed intake, and the added complications in accurately measuring individual forage intake in the pastoral environment, individual data collection primarily occurs at test facilities with expensive specialized equipment, increasing expressed interest in developing methodologies to accurately identify feed efficient animals on a large scale (Herd et al., 2003).

Genetic Covariances

Phenotypic RFI is the most common net feed intake index calculated given the relative simplicity of measuring phenotypic parameters during the growth phase. This creates the possibility of focusing solely upon the physical parameters associated with feed efficiency and ignoring the genetic component altogether (Kennedy et al., 1993). In general, the genetic covariance of RFI increases as the heritability of feed intake increases, becoming more positive as the correlation between production traits and feed intake improves. Using genetic covariance’s in the RFI model yields an index genetically independent from production. The utilization of genetic covariance’s is only critical when there is an environmental by genetic interaction in the prediction of feed intake (Kennedy et al., 1993). However, Archer et al. (1998) found phenotypic RFI to be independent of growth at a genetic level in mice even though the social litter environment was a significant factor. But post-weaning RFI was highly correlated (0.60) with mature feed intake but weakly correlated with body composition (0.17) indicating the value of post-weaning studies and minimal effect on mature composition (Archer et al., 1998). Since phenotypic vs genetic residual feed intake correlated 0.98 and 0.96 post-weaning and mature respectively (Archer et al., 1998), the added work of using genetic covariance may be unnecessary, providing animals are tested in uniform cohorts to limit interactions. This may be preferable, as utilizing the genetic component limits the opportunity for genetic progress due to the controlling of the error associated with genetic make-up.

Impact of RFI on Body Composition and Carcass Traits

Published feed intake studies (Nkrumah et al., 2004; Robinson and Oddy, 2004; Schenkel et al., 2004; Lancaster et al., 2009b) analyzing associations between growth composition and RFI in beef cattle indicate feed efficient (low-RFI) cattle tend to deposit less fat than less efficient (high-RFI) cattle. Correlations between back fat thickness (BF) and RFI were moderately positive (Richardson et al., 2001; Nkrumah et al., 2004; Richardson and Herd, 2004; Lancaster et al., 2009b), but weak in beef cattle, while longissimus muscle area correlations were weak but more variable, ranging from negative to positive (Richardson et al., 2001; Basarab et al., 2003; Nkrumah et al., 2004; Schenkel et al., 2004). Inclusion of carcass traits into the RFI model using multiple linear regression indicates that gain in BF explains the most variation in feed intake, but only had a minor reduction in the SD (Lancaster et al., 2009b). The consensus from the literature seems to suggest that selection for animals using RFI will have minimal impact on composition of gain, though a reduction in BF may be observed.

Feeding Behavior and Activity

Feed-related behavioral responses can alter physical activity and thus influence total energy expenditure and feed efficiency (Adam et al., 1984; Susenbeth et al., 1998). Time spent eating is the main predictor of energy expenditure associated with feed, an observation first made by Dahm (1910) and reinforced by Susenbeth et al. (1998). This allows not only for reduced energy expenditure by the animal via manipulating the presentation of the feed via milling and mixing, but can also explain the variation between energy requirements and feed consumption in animals who inherently vary in the time spent feeding (Herd et al., 2004; Richardson and Herd, 2004).

Modern technology such as the GrowSafe® feed intake system used in most intake trials has made the economic collection of feeding behavior attainable for livestock producers. The GrowSafe® system records feeding events, meal events, and daily intake from raw data transmitted wirelessly from the feed bunk to a personal computer running the specialized data acquisition (DAQ) software. Bunk visit frequency, the count feeding events daily, and duration, the summation of feeding events, are summarized from the behavior tables into daily totals. Head down duration is an attempt to calculate the total amount of time the animal had its head in the bunk and is the number of EID reads multiplied by the read rate of the system. Grouping of bunk visits into meals is best accomplished by using a Gaussian-Weibull distribution model to bunk visit behavior, measuring the lowest intersect between the feeding non-feeding intervals determine the most biologically relevant meal criterion for each animal (Bailey et al., 2012). A meal criterion determines the maximum time separating bunk visits which grouped into one biologically relevant meal event. Eating rate is derived by dividing total day feed intake by total daily bunk visit duration, creating a ratio grams/min (Durunna et al., 2011) and though phenotypically correlated with feed intake (Lancaster et al., 2009a), are more variable and less reliable than bunk visit frequency, bunk visit duration, and head down duration.

Inclusion of feeding behavior traits in the model predicting the RFI can reduce the mean squared error (MSE%) and increase R^2, improving the ability to account for portions of the variation left unexplained by metabolic BW and ADG. However, which traits are found to be significant and what percentage of the variation is explained varies from study to study. Nkrumah et al. (2014) reported 43% and 65% difference between high vs. low RFI class groups in bunk visit duration and bunk visit frequency behavior exhibited in Charolais by Angus steers. But in an earlier paper, Nkrumah et al. (2007) reported that more efficient heifers spent 24% less time at the bunk and Montanholi et al. (2009) stated that steers classified as low RFI had significantly less bunk visits with a slower eating rate than their less efficient mates. Basarab et al. (2003) reported a decrease of 6.67% from high to low RFI. However, Bingham et al. (2009) contradicted these findings, reporting that efficient animals had 15.06 vs. 14.75 bunk visits for high RFI animals. This may be due to different genetic backgrounds as these were Brangus heifers, or gender, as Lancaster observed bulls and Nkrumah and Durunna reported their findings on steer studies.

In short, feeding behavior duration, frequency and rate are moderately repeatable (0.37 to 0.62 (Kelly et al., 2010)), heritable (h2 = 0.28 to 0.38, (Nkrumah et al., 2007b)), and have moderate to strong correlations with RFI feed efficiency (Basarab et al., 2013). The increase in feeding activities results in a 2 — 5% increase in energy expenditure in feeding activities (Herd et al., 2004; Basarab et al., 2011). However, a standardized methodology to analyze the importance of highly correlated traits needs to be researched to increase the usability of feeding behavior to identify and select more efficient animals for further study and production.

Partial Least Squares Regression Analysis of Feeding Behavior Traits

Feeding behavior has been shown to explain up to 35% of the variation associated with DMI in growing and finishing cattle using multiple linear regression analysis (Lancaster et al., 2009; Kayser and Hill, 2013). However, multiple linear regression fails to account for the multi-collinear nature of feeding behavior, which has limited the ability to utilize feeding behavior traits to explain additional variation in DMI for the base RFI model. Partial least squares regression analysis (PLS), also known as projection to latent structures, is the regression extension of principal components analysis (PCA) and provides a philosophically solid means of analyzing multi-factorial datasets with varying degrees of collinearity and deciphering complex synergistic and competitive mechanisms (Wold et al., 2001; Erikson et al., 2006a). Analysis begins by mean centering all variables with equal variance. Next, mean centered variables are projected onto new variables, referred to as components or as latent factors) consisting of a linear combination of the original variables with coefficients, (weights) deemed to be a good predictors of the dependent variable(s) (Garthwaite, 1994). These components are then used as the independent variables in the regression equation to predict the dependent variable(s) with each successive component accounting for a lower proportion of the original variance (Garthwaite, 1994; Wold et al., 2001; Eriksson et al., 2006a). These weights are useful in determining the direction and value of the modeled biological responses (Eriksson et al., 2006a). The primary purpose of using PLS analysis is to predict biological outcomes based upon input from multiple highly related variables by accounting for their interaction and compressing them into a few relevant components (Eriksson et al., 2006b).

As in any empirical modeling, it is critical to achieve appropriate model complexity by determining the appropriate number of variables and components to include in the final prediction equation (Wold et al., 2001). Evaluation of models containing different combinations of components is accomplished by using the predictive residual sum of squares (PRESS) statistic (JMP12 Multivariate Methods; Wold et al., 2001). Variables were selected if the variable of importance (VIP) score was greater than 0.8 (Wold et al., 2001).

There is some discrepancy in the literature pertaining to omission of original independent variables. Researchers have utilized the magnitude of the coefficients, the VIP scores above a threshold of either 0.8 (Wold et al., 2001) or 1.0 (Geladi and Kowalski, 1986) or both to identify variables that are retained in the model. However, removal of predictor variables from the model often removes important information from the model, which may result in the model being less robust (Wold et al., 2001; Eriksson et al., 2006b). Thus, caution should be exercised when variables are removed from a model. In large multivariate datasets, all the independent variables carry a certain proportion of the information about the dependent variable. Since most variables will not contain more information than the noise level, no or only mild reduction in goodness-of-fit results may be experienced due to their removal. Additionally, variable removal may result in other variable correlations becoming more important, further contributing to the goodness-of-fit characteristics as other independent variables take over the importance previously explained by those that have been deleted. This shift can influence the interpretation of the model and diminish the usability of the model for future observations that may present a slightly different correlation structure. One might consider the reason a variable does not explain a significant portion of the variation may be due to absence of variation present within the current dataset. However, if a future observation is a significant outlier, the ability to identify the outlier will be lost (Eriksson et al., 2006b).

Partial least squares analysis has gained popularity with the accumulation of large, and sometimes incomplete datasets, with a multitude of variables (Eriksson et al., 2006a). Primary use has been in spectorial analysis, however, it has served alternative purposes, including the development of prediction models to determine body composition using ultrasound (Peres et al., 2010), particle size distribution (Blanco and Peguero, 2008) and chemical composition, intake and digestibility of feed (Huntington et al., 2011). Additionally, PLS has been used to generate predictive equations to profile nutritional characteristics of feedstuffs based on NIRS analysis of feeds (Huntington et al., 2011), and voluntary intake of cattle via NIRS analysis of fecal samples (Johnson et al., 2017).

Few studies to date have used PLS analysis to examine the associations of animal behavior traits and various phenotypes. The relationship between social status and boldness in zebra fish in various environments was determined by measuring multiple behavior traits (Dahlbom et al., 2011). A PCA plot of the behaviors showed the degree of correlation between measured variables and solidified previously understood behavior relationships. In humans, a PLS model utilizing 18 previously described developmental and social behaviors was used to examine the relationship between caffeine consumption and impulsive behaviors (Grant and Chamberlain, 2018). In both cases, PCA and PLS analysis allowed for identification and selection of behavior traits pertinent to explaining the desired independent variable, despite autocorrelation issues within the original multivariate dataset.

Montanholi et al. (2009) used PLS analysis to examine biological factors that explained between-animal variation in RFI. Results based on PLS analyses revealed that between-animals differences in feeding behavior traits, multiple infrared thermography measurements, and glucocorticoids concentrations accounted for 18, 59, and 7% of the total variation associated with RFI, respectively. These classes of traits have usefulness in the indirect assessment of feed efficiency in cattle. Among them, IR thermography appeared to be the most promising alternative to screen cattle for this feed efficiency. These findings might have application in selection programs and in the better understanding of the biological basis associated with productive performance.

With the increasing availability of biosensor systems capable of monitoring individual-animal behavioral responses, there is a need to refine analytical methods of large databases containing multivariate behavior traits to provide more economically relevant information. Understanding the ability of alternative statistical methods such as principal components analysis and its extension, partial least squares regression, will provide the industry with more tools to address these questions. However, there is a need to research the abilities and limitations of various behavior monitoring devices to obtain a better understanding as to how the behaviors are identified, and the accuracy with which a device is able to predict and detect an animal's behavior.

Behavior Monitoring

Animal behavior offers important insight into an animal's current metabolic state (Weary et al., 2009) and has been used to assess the health status (Quimby et al., 2001), feed intake (Tolkamp et al., 2000; Kayser and Hill, 2013), feed efficiency (Lancaster et al., 2009; Hafla et al., 2013) and bunk competition (Devries et al., 2003). The majority of the commercial systems currently available are based on variants of RFID technology, with sensors specifically designed to capture the animal's presence or absence from a feed alley (Schwartzkopf-Genswein et al., 1999; Devries et al., 2003; Wolfger et al., 2015), or from an open (Chapinal et al., 2007; Krawczel et al., 2012) or gated feed bunk (Lancaster et al., 2009; Mendes et al., 2011). System developers have primarily focused from on technology to capture both feed intake and feeding behavior, which includes the GrowSafe® feed intake system validated by Mendes et al. (2011), and the Insatec® system validated by Rushen et al. (2012). Both flagships systems are different in their inherent design, but are similar in function, as both record the animal's presence at the bunk and measure feed disappearance while the animal is present. Recording BV events allows the computation of feeding behavior traits such as BV frequency and duration which are proven to be biologically relevant in numerous studies.

The GrowSafe® feed intake system was validated by Schwartzkopf-Genswein et al. (1999) and Mendes et al. (2011) using time-lapse video recordings to obtain observational data to validate the accuracy of the system to measure frequency and duration of BV or meal events in beef cattle. Schwartzkopf-Genswein et al. (1999) used 6 crossbred heifers to validate the GrowSafe® system with a static 85-sec meal criterion and reported a total daily error rate of 6% with a correlation R^2 of 0.96 between visually observed and electronic data for both meal frequency and duration. Mendes et al. (2011) evaluated 10 randomly selected animals from a group of 32 Brangus heifers during a 6-d period. Observed (time-lapse video) and electronic BV frequency and duration resulted in a coefficient of determination value of 0.68 and 0.81 respectively. Evaluation of the systems accuracy in determining the animal's presence or absence at a min resolution was 86.4 and 99.6% for sensitivity and specificity, respectively. Chapinal et al. (2007) evaluated the accuracy of the Insentec® feed intake system using time-laps video recording to observe 42 Holstein cows. The coefficient of determination for BV frequency was 0.99, while the accuracy of the system was found to be 100 for both sensitivity and specificity respectively (Chapinal et al., 2007). This is notably better performance than that reported by the GrowSafe® feed intake system, however, the Insentec® system consists of an air-operated gate, which is automatically opened when the animal's EID tag is detected by the system. Therefore, the system must correctly identify the animal prior to admission to the feed bunk, whereas the GrowSafe® system has no such means of refusing animal access to the feed bunk.

Devries et al. (2003) evaluated the accuracy of the GrowSafe® feed alley monitoring system designed to record bunk visit behavior of dairy or beef cattle as they approached an open feed bunk. Systems of this type have been slower to develop due to issues with interference between animals and the structural components of the feeding area (e.g., concrete, metal) and, their inability to measure feed intake. The accuracy of the system was diminished compared to the feed intake system, with sensitivity and specificity values of 87.2 and 99.6%, respectively. Few other systems of this sort are found in the literature, though Wolfger et al. (2015) evaluated the FEDO® system which utilizes a bracelet containing and RFID tag with an accelerometer which is worn on the front pastern and senses proximity to a sensor located within the feed bunk. This system reported a coefficient of determination for BV frequency of 99.0% and accuracy of 100 and 94% of sensitivity and specificity, respectively, and offers the added advantage of reporting additional behavior traits other than feeding behavior (Wolfger et al., 2015).

Animal behavior is directly related to important metabolic processes that have varying degrees of relevance to the producer. As technology improves alongside our understanding of the interaction between animal welfare, efficiency and behavior, the opportunity to improve the industry's production efficiency will present itself. This not only lies in increasing the accuracy of identifying sick animals based upon deviations from normal behavior, but also identifies key heritable behavior traits indicative of animals with higher economic value to the producer.

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CHAPTER II

VALIDATION OF A HIGH FREQUENCY ELECTRONIC RFID SYSTEM FOR MONITORING FEEDING BEHAVIOR IN BEEF CATTLE

Introduction

Feeding behavior data in beef cattle has traditionally been collected via time-lapse video or the use of expensive electronic feed bunks that limit wide spread applications in research or the commercial beef industry (Chizzotti et al., 2015). Understanding feeding behavior patterns between animals provides insight into feed intake (Tolkamp et al., 2000; Kayser et al., 2013), feed efficiency, (Lancaster et al., 2009; Hafla et al., 2013; Fitzsimons et al., 2014), and the onset of disease (Jackson et al., 2015; Quimby et al., 2001; Weary et al., 2009). Multiple systems based upon various RFID technologies have been developed to monitor feeding behavior in confined cattle, including those that measure bunk attendance from feed alleys (Schwartzkopf-Genswein et al., 1999; DeVries et al., 2003; Wolfger et al., 2015) and bunk attendance from open (Lancaster et al., 2009), or gated feed bunks (Chapinal et al., 2007; Krawczel et al., 2012). Further, various systems monitor feed intake as well as feeding behavior, including the GrowSafe® feed intake system, which was validated by Mendes et al. (2011), and the Insentec® system (Chapinal et al., 2007). While all of these systems differ slightly in their inherent design by seeking to quantify the frequency and duration of bunk visit (**BV)** events by the animal.

However, industry adoption of these technologies has been slow because of infrastructure and cost limitations. Signals used to detect animal presence and transmit data can be lost due to interference with common obstacles such as water, concrete and steel. Many systems require installation of structures that alter animal behavior, limit feed bunk capacity, and may present risks to their welfare. Furthermore, installing and maintaining this equipment can be cost prohibitive, and may not provide an economic advantage to the operation. Therefore, there is a need to develop new technologies that complement existing feed yard infrastructure while providing relevant information to the operation. Objectives of this study were to validate individual-animal feeding behavior data collected from the CattleTraq® system through comparison with time-lapse video recordings, and to determine if changes in the parameter settings used to define an electronic BV event affects the accuracy of feeding behavior data.

Materials and Methods

Animals and Housing

All animal care and use procedures were in accordance with the guidelines for use of Animals in Agriculture Teaching and Research as approved by the Texas A&M University Institutional Animal Care and Use Committee.

Five Angus-crossbred cows, with an initial BW of 537 ± 50 kg were used in this study. Upon arrival, cows were fitted with ultra-wideband radio frequency identification (RFID) ear tags (ABGI Tag and Traq®, Greeneville, TX) and a foam sticker of unique shape and color to allow for individual identification on the video. Cows were housed in a pen (9 x 26 m) equipped with a water trough, and fence line bunk (4.88 m) at the Beef Cattle Systems Research Center (College Station, TX). Cows were provided ad libitum access to a roughage-based diet fed twice daily at approximately 0800 and 1500.

A video surveillance camera was affixed 2.89 m above and 0.91 m in front of the center of the bunk to record animals entering and exiting the feed bunk (Figure 2.3). A 500-W light was placed above the feed bunk to facilitate collection of video at night. Two trained observers independently observed the time-lapse video, and recorded animal identification number and the start and end times for each BV event using Behavioral Observation Research Interactive Software (Friard and Gamba, 2016). Start and end times for BV events were recorded when an animal's poll had completely transverse the horizontal cable extending above the lip of the feed bunk. There was no attempt to quantify the orientation of the head during a BV event.

The CattleTraq® System

The electronic (CattleTraq®) system used for this study consists of a computing ecosystem (hardware and software) that provides real time positional information of each animal within the pen. The hardware consists of an ultra-wide band transmitter attached to the calf via an ear tag, and readers positioned around the pen and in a beacon tube (Figure 2.3) fixed to the front face of the feed bunk that receive tag positional information at 1-s intervals and relays back to a central server. The beacon tubed contained 6 radio receivers spaced 0.91 m apart. A seventh radio receiver was affixed approximately 2.89 m above the center, and 0.91 m away from the front of the bunk. Computer algorithms evaluated the positional information of each calf and continuously recorded the presence or absence of an animal from the feed bunk according to various parameter settings.

Data Analysis

The electronic (CattleTraq®) algorithm was used to calculate the BV data according to the parameter settings used to define the presence or absence of an animal from the feed bunk. The system initiated a feeding event when it detected the ear tag of an animal to have crossed the lip of the feed bunk, which was defined in the computer as a virtual line extending along 0 according to the y axis. The computer terminates a BV event when the animal is detected to have left the feed bunk, defined by the maximum distance a tag can be detected from the bunk on the y axis without ending the current BV. The purpose of the out-of-bunk parameter setting is to avoid the over or under estimation of BV frequency and duration due to the animal flipping the ear out of the bunk while consuming feed. Out-of-bunk parameter settings were computed at values of 0, 15, 25, 30, and 35 cm out, then electronic BV frequency and duration were compared to observed feeding behavior. A total of 280 animal h of observed video were decoded, and the corresponding electronic data captured.

The frequency of BV events was calculated as the number of times the animal visited the bunk during within a h. Bunk visit duration was computed as the sum of the differences between the timestamp recorded as the animal entered the bunk and the timestamp recorded as the animal left the bunk per hour.

Statistical and Sensitivity Analysis

The observed or electronic data collected for each animal h was considered the experimental unit for all data analyzed in this study. Observed (video) and electronic (CattleTraq®) measurements of feeding behavior were compared using a PROC MIXED model (JMP, SAS Institute Inc., Cary, NC) that included treatment (0, 15, 25, 30, and 35 cm out-of-bunk parameter setting) as a fixed effect. Observed data (dependent variables) were regressed on electronic feeding behavior data (independent variables) to obtain an estimate of precision (**R^2**). In addition, the mean square error of prediction (**MSEP**), mean bias (**MB**), model accuracy (**Cb**), and concordance correlation coefficient (**CCC**) were computed to assess the precision and accuracy of the electronic system in predicting BV traits using the Model Evaluation System as described by Tedeschi (2006). As described by DeVries et al. (2003), sensitivity (the likelihood that an animal present at the feed bunk is detected present by the system) and the specificity, (the likelihood that an animal absent from the feed bunk is detected absent by the system) were evaluated by determining feed bunk presence and absence of observed and electronic BV duration for each second of the day during video recording periods.

Results

The observed and electronic BV frequency and duration data are presented in Table 2.1. The out-of-bunk parameter setting affected ($P < 0.01$) BV frequency and duration. As demonstrated in Figure 2.1, BV frequency decreased, and BV duration increased as the out-of-bunk parameter setting was increased. However, electronic BV frequency at out-of-bunk parameter settings 0 cm out and 15 cm out were greater ($P < 0.05$) than observed BV frequency, while no differences were detected ($P > 0.05$) at out-of-bunk parameter settings 25, 30, and 35 cm. Bunk visit durations at out-of-bunk parameter settings 15, 25, 30, and 35 cm were not different from observed values ($P > 0.05$), whereas, electronic BV duration at out-of-bunk parameter setting 0 cm out was less ($P < 0.01$) than observed BV duration.

The decrease in frequency and increase in duration of electronic BV events as the out-of-bunk parameter setting increased from 0 to 35 cm out can be explained by how this parameter setting is used by the computer software to determine the conclusion of BV events. When measuring a BV event, the end time stamp of the BV event was recorded when the geo-location of the tag is detected beyond the value specified by the out-of-bunk parameter setting. Consequently, the frequency of BV events will decrease as the distance from the bunk used to end a BV event is increased. Conversely, since fewer BV are created, the duration of BV will increase as the out-of-bunk parameter setting is increased.

The purpose of using the out-of-bunk parameter setting is to limit the over or under prediction of BV frequency and duration if the geo-location of the tag is not accurate while the animal is consuming feed.

The evaluation of the goodness-of-fit of the system to predict observed BV frequencies and duration are summarized in Table 2.1. The out-of-bunk decision rules of 25, 30, and 35 cm out reported higher values for precision and accuracy of the system to predict bunk visit frequency compared to the other out-of-bunk decision rules. This was determined by a greater R^2 (81.0% for 25, 30, and 35 cm out, respectively) lower SD (11.04, 9.98, and 11.04) and less mean bias (0.07, -0.9, and 0.07) for out-of-bunk rules 25, 30, and 35 cm, respectively. The out-of-bunk decision rules 25, 30, and 35 cm improved values for prediction of bunk visit duration. This was determined by a greater R^2 (89.0, 90.0, 90.0%) and less mean bias (-1.12, -0.68, -0.33) for out-of-bunk decision rules 25, 30, and 35 cm, respectively. This indicates that multiple out-of-bunk decision rules can accurately predict at the same time BV frequency and duration.

To examine the sensitivity and specificity of the system to predict BV data, the BV duration was summarized using a binary coding system where an animal was considered either present or absent at the feed bunk for every second of the observed hour (N = 3600 sec total) during the 280 observed h (Table 2.2). This was calculated for the out-of-bunk decision rules 0, 15, 25, 30 and 35 cm. The sensitivity of the system was 61.6, 76.1, 76.6, 84.4 and 82.0% for out-of-bunk decision rules 0, 15, 25, 30, and 35 cm, respectively. The specificity of the system was 99.3, 98.8, 98.8 98.3, and 98.5% for 0, 15, 25, 30, and 35 cm out, respectively.

Discussion

Results of this validation study demonstrated that the system can accurately predict the frequency and duration of observed BV events using an out-of-bunk decision rule between 25 and 35 cm. Further evaluation of the data indicates that using an out-of-bunk rule 30 cm is the most accurate for predicting BV frequency. However, there was no advantage of this rule regarding calculating and predicting BV duration.

Previous studies have validated the use of electronic active and passive RFID-based systems in cattle. Bach et al. (2004) evaluated the accuracy of feeding behavior data collected by a gated feed intake system and reported a sensitivity and specificity of 99.6 and 98.8%, respectively. Chapinal et al. (2007) validated the FB data collected by the Insentec® System, which consists of a gated feed bunk activated by an RFID tag and allows continuous observation of BV frequency, duration and feed intake. Due to the extremely structured feeding area of the Insentec® System, the study reported strong coefficients of determination for bunk visit (99.0%) and perfect (100%) sensitivity and specificity. DeVries et al. (2003) and Schwartzkopf-Genswein et al. (1999) validated an early version of a GrowSafe® system feed bunk monitoring system which used a mat attached to a standard feed bunk to record only feeding behavior. DeVries et al. (2003) reported sensitivity and specificity values of 87.4 and 99.2%, respectively; however, coefficient of determination values was not reported. The Intergado® feed intake system reported a coefficient of determination of 99.0% for BV duration and sensitivity, specificity values of 99.6 and 99.9%, respectively. Mendes et al. (2011) validated the GrowSafe® feed intake system and reported coefficients of determination for BV frequency and bunk visit duration of 68.0 and 81.0%, respectively. Sensitivity and specificity were analyzed by detecting the animal's presence on a per minute basis, resulting in values of 86.4 and 99.6%, respectively. Analyzing the accuracy of the system on a second basis as done in the current study drastically increases the opportunity for wrong determination. Given that the this study's values are greater than those reported, these results suggest that the electronic system has the capability to accurately detect an animal's presence at the feed bunk.

Recent advances in ultra-wideband RFID and computing technologies have increased the availability of biosensor systems that track feeding behavior in less structured feed bunk systems than the feed intake systems presented previously. Brown-Brandl et al. (2011) developed a system of passive RFID tags that communicated with RFID transceivers located in pipes fastened to the top of the bunk. While a 94.1 and 98.3% agreement with observed frequency and duration was achieved, inclement weather and infrastructure interference within the bunk were noted.

Wolfger et al. (2015) reported validation statistics for the FEDO® system, which consists of a tracking band containing an accelerometer and a RFID tracking chip detected by antennae located near the bottom of the feed bunk as the animal approaches. It was reported that BV frequency had a coefficient of determination of 99.0%, and sensitivity and specificity of 100 and 94.0%, respectively. These results were better than what was found using the current electronic system, although it should be noted that that a 5-min static meal-criterion, which combined bunk-visits less than 5-min apart into one BV event, lowered resolution compared to the electronic system. The greater resolution of the electronic system increases the opportunity for inconsistencies with observed data to occur since less cleaning of the data is performed creating a more precise picture of individual feeding behavior.

Differences in the RFID-based systems and methodology used to evaluate the data should be considered when comparing each system's ability to detect an animal's presence or absence from the bunk. An open feed bunk (such as that used in this study), is standard in the industry and allows the animal to freely perform their individual feeding behavior patterns (DeVries et al., 2003), however, these types of feed bunks can increase the difficulty in in predicting BV events. Thus, the accuracy of the current system makes it a truly unique tool to monitor feeding behavior, with a wide array of applications in the feed lot industry.

Implications

The accuracy and sensitivity of the system exceeds the standards of acceptability set by previous technologies. The electronic system accurately measured animal presence at the bunk and BV frequency and duration, however, implementing the system is not trivial. Set-up and calibration requires substantial input and expertise, and the inherent nature of the RFID technology causes signals to be lost due to interference from metal and other objects. This technology offers the ability to better understand feeding patterns, which provides the opportunity to improve selection of feed efficient animals, predict onset of disease in animals, and facilitate improved bunk management practices to improve animal performance.

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Table 2.1 Goodness of fit statistics between electronic and observed bunk visit (**BV**) frequency and duration at various out-of-bunk decision rules.

Trait	Mean	SD	R^2	MSEP[1]	Mean Bias[2]	CCC[3]
BV frequency, events/h						
Observed	8.65[a]	11.1	-	-	-	-
0 cm out	19.22[b]	24.66	71.67	388.00	10.57	0.54
15 cm out	12.61[c]	16.01	76.33	88.29	3.96	0.78
25 cm out	8.72[a]	11.04	81.32	25.99	0.07	0.90
30 cm out	7.75[a]	9.98	81.05	22.89	-0.90	0.90
35 cm out	8.72[a]	11.04	81.32	25.59	0.07	0.88
BV duration, min/h						
Observed	6.84[a]	7.97	-	-	-	-
0 cm out	4.3[b]	5.51	86.07	17.28	-2.54	0.82
15 cm out	5.03[ab]	6.34	87.98	10.85	-1.81	0.90
25 cm out	5.72[ab]	7.08	89.24	7.40	-1.12	0.94
30 cm out	6.16[ab]	7.42	89.96	6.60	-0.68	0.94
35 cm out	6.51[a]	7.65	89.94	6.44	-0.33	0.95

[abc] values separated by different letters with column are different $P < 0.01$; [1]MSEP = mean squared error of prediction; [2]Mean Bias = absolute mean difference observed – predicted; [3]CCC = concordance correlation coefficient.

Table 2.2 Sensitivity, specificity, and accuracy of the electronic system to predict bunk attendance at the feed bunk using various out-of-bunk decision rules.

Out-of-bunk decision rule	Sensitivity[1]	Specificity[2]	Accuracy[3]
0 cm out	61.60	99.30	80.45
15 cm out	76.11	98.83	87.47
25 cm out	76.60	98.80	87.90
30 cm out	84.43	98.33	91.38
35 cm out	82.09	98.52	90.31

[1]Sensitivity = true positive rate, percent of time the system correctly classified the animal as present in the feed bunk; [2]Specificity = true negative rate, percent of time the system correctly classified the animal as absent from the feed bunk; [3]Accuracy = overall system accuracy, the average of sensitivity and specificity at that out-of-bunk decision rule.

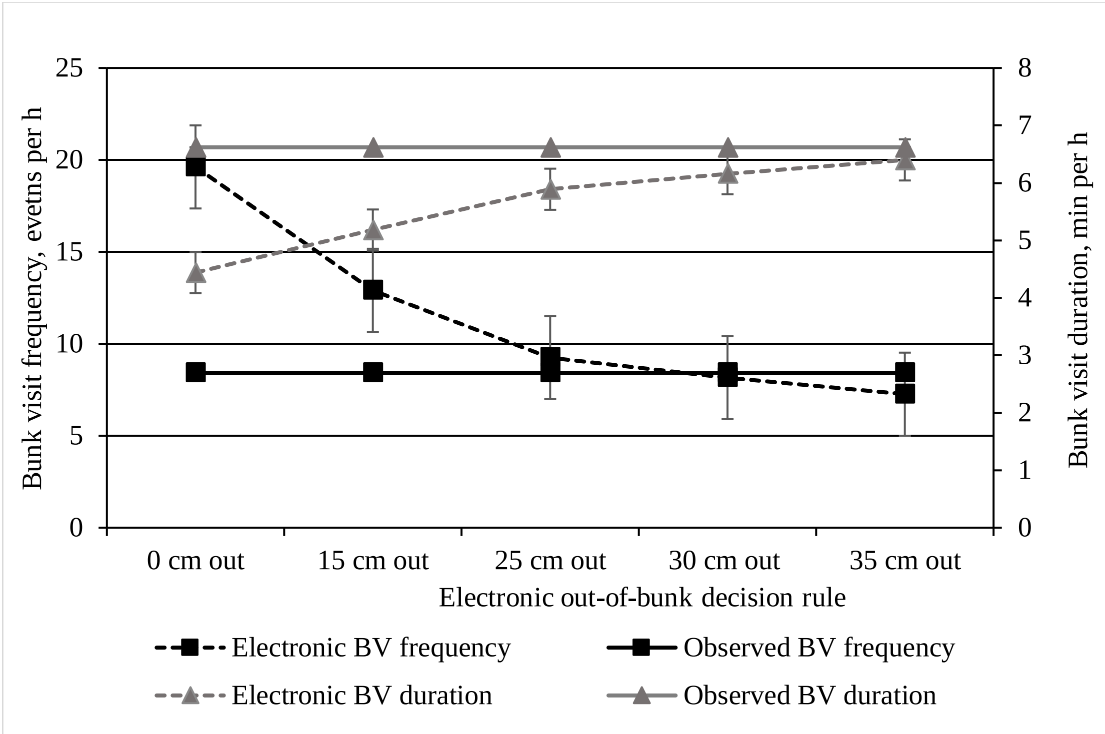
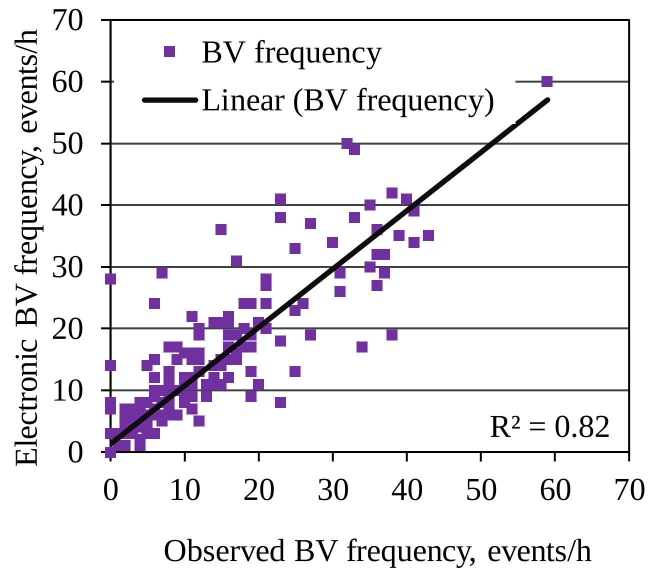


Figure 2.1 Means (± SE) of electronic vs. observed bunk visit (**BV**) frequency and duration at various out-of-bunk decision rules.



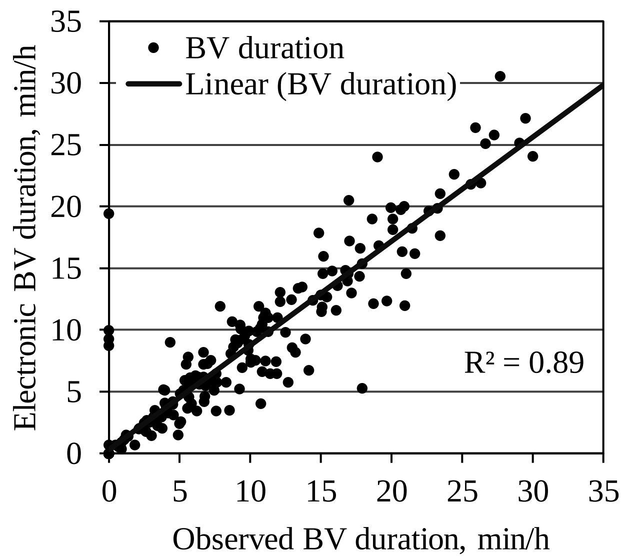


Figure 2.2 Electronic vs. observed bunk visit (**BV**) frequency (top panel) and duration (bottom panel) at the selected out-of-bunk decision rule (30 cm).

Figure 2.3 View of the feed bunk (left panel) and the beacon tube (right panel) used to capture electronic and observed feeding behavior in this study.

CHAPTER III

PREDICTION OF FEED INTAKE AND FEED EFFICIENCY IN FEEDLOT STEERS BASED ON PHENOTYPIC ASSOCIATIONS WITH FEEDING BEHAVIOR AND CARCASS ULTRASOUND TRAITS

Introduction

Increasing the genetic merit of beef cattle for feed efficiency is an effective strategy to improve the economic and environmental sustainability of beef production. Residual feed intake (**RFI**) is a measure of feed efficiency independent of performance and body weight (**BW**), whereby feed-efficient animals consume less dry matter intake (**DMI**) than predicted (Arthur et al., 2001). Since RFI is moderately heritable (Arthur et al., 2001; Herd et al., 2003; Crowley et al., 2010), it is an ideal trait used to improve efficiency of feed use and independent of productivity traits (Carstens, 2006), it is more robust compared to other selection traits that are correlated with increased mature BW. However, the complex biological mechanism controlling feed intake have resulted in an incomplete understanding of the RFI (Herd and Arthur, 2009). Furthermore, the technology required to measure individual animal feed intake is only possible through the use of expensive equipment (Moore et al., 2014), limiting application in replacement females.

Numerous studies have documented that cattle with divergent RFI phenotypes exhibit distinctly different feeding behavior (**FB**) patterns (Lancaster, et al., 2009), indicating that cattle feeding behavior could serve as a bio-marker for selecting for feed efficient animals (Hafla et al., 2013; Nkrumah et al., 2014; Wood et al., 2014). Historically, feeding behavior traits have been difficult and expensive to measure, however, advancements in high frequency RFID technology combined with improved battery design and wireless data transmission systems increase the likelihood that these technologies designed to continuously monitor individual animal behavior will be adopted at the commercial scale.

Advanced animal tracking systems have the potential to record continuous activity and feeding behavior. Multiple studies published in the literature identify feeding behavior traits such as head down (**HD**) duration, HD duration per meal (Kayser et al., 2013), bunk visit (**BV**) frequency (Lancaster et al., 2009), and BV duration (Fitzsimons et al., 2014) to be predictive of RFI. However, the signals between feeding behavior traits, performance and RFI are variable between studies (Kayser et al., 2013), as Nkrumah et al. (2007), Basarab et al., (2003), and Durunna et al., (2011) reported differences in BV frequency between RFI classes, while none are reported by Kayser et al. (2013), thus, isolating specific feeding behavior traits for use in prediction equations is difficult (Kayser et al., 2013). Moreover, because feeding behavior traits are collinear, the use of multiple linear regression techniques to create prediction equations is limited. Partial least squares (**PLS**) regression is designed to create prediction equations from multivariate datasets containing highly collinear variables, therefore, PLS regression may be an effective method for predicting RFI from feeding behavior data. The objectives of this study were to examine the associations between RFI, FB patterns and ultrasound traits in beef steers and, to evaluate the variation in RFI explained by FB and ultrasound traits using PLS regression methods.

Materials and Methods

Animals and Experimental Design

All animal care and use procedures were in accordance with the guidelines for use of Animals in Agriculture Teaching and Research as approved by the Texas A&M University Institutional Animal Care and Use Committee.

This study was comprised of 3 trials conducted with composite Angus steers (N = 508; Rex Ranch, Ashby, NE), with an initial BW of 309 ± 56 kg and age of 290 ± 16 d. Upon arrival at the Texas A&M AgriLife McGregor Research Center (McGregor, TX), steers were vaccinated, dewormed and fitted with passive, half-duplex transponder ear tags (Allflex USA Inc., Dallas TX). Steers were randomly assigned to 1 of 2 pens (46 x 58 m) equipped with 10 electronic feed bunks (GrowSafe Systems LTD., Airdrie, AB, Canada) to measure feed intake and FB. Steers were adapted to a high-grain diet (Table 3.1) for 28 d, after which *ad libitum* feed intake and FB data were collected for 70 d. The GrowSafe® system consisted of feed bunks equipped with load bars to measure feed disappearance, and an antenna within each bunk to record animal presence by detection of the animal's unique EID tag during feeding events.

Individual feed intake was computed using a subroutine of the GrowSafe 4000E software (Process Feed Intakes) based on continuous recordings of feed disappearance during feeding events. Assigned feed disappearance (**AFD**) rates were computed daily for each feed bunk to assess data quality. Data was excluded due to equipment malfunction or when the average AFD rates were < 95% for the pen. For trial 1, 15 and 11 d were excluded for pen 1 and 2, respectively, while 22 and 4 d were excluded for trial 2, and 12 and 15 days were deleted for trial 3, in pens 1 and 2, respectively. The average AFD for the days included in analysis were 98.3, 98.8, and 97.3% for trials 1, 2 and 3, respectively.

Feeding behavior traits evaluated in this study were based on the frequency and duration of individual animal bunk visit and meal events. Further, the duration of non-feeding intervals (**NFI**), head down duration, latency to the bunk following feed delivery (**TTB**), and the corresponding day-to-day variation (**SD**) of these traits were measured for each animal (Table 3.2). A BV event commenced when the EID tag of an animal was first detected at a feed bunk and ended when either the duration of time between the last 2 consecutive EID recordings exceeded 100-s (a parameter setting in the GrowSafe 4000E software [GrowSafe Systems Ltd.]), the EID tag was detected in another bunk, or the EID ear tag of another animal was detected at the same bunk (Mendes et al., 2011).

Bunk visit frequency was defined as the number of independent BV events recorded regardless of whether feed was consumed; and BV duration was defined as the sum of the lengths of BV events recorded during a 24-h period (Jackson et al., 2016). The interval lengths between BV were defined as the non-feeding interval (**NFI**), and the maximal NFI was defined by the longest NFI within each day. Head down duration was computed as the sum of the number of times the EID ear tag for an animal was detected each day multiplied by the scan rate of the GrowSafe system (1.0 readings/s; Jackson et al., 2016).

A 2-pool Normal-Weibull distribution model was fitted to the feeding and non-feeding interval data collected over the duration of the study. The intercept of the 2 distributions was used to define meal criterion, that included the longest non-feeding interval that is still part of a meal (Yeates et al., 2001). Bunk visit event data was clustered into meal events after meal criterion was determined for each animal using the BV events from the duration of the study (Bailey et al., 2012). Meal frequency was defined as the total number of meal events per 24-h period, and meal duration was defined as the sum of the lengths of meals recorded during a 24-h period. In addition, the day-to-day variation of individual animal BV frequency, BV duration, HD duration, TTB, meal frequency, and meal duration were computed as the SD of the residuals from the actual vs predicted values. These values were calculated by regressing trait on day of trial. Additionally, 3 ratio traits were calculated; BV frequency per meal event, HD duration per meal event, and HD duration per BV event.

During the 70-d trials, BW was measured at 14-d intervals, and ultrasound measurements of backfat depth, intramuscular fat, and LMA were obtained on days 0 and 70 by a certified technician using an Aloka 500-V instrument with a 17-cm, 3.5-MHz transducer (Corometrics Medical Systems Inc., Wallington, CT). Diet samples were collected weekly and composited by weight at the end of each trial. Diet DM was measured by drying samples in a forced air oven for 48-h at 105 °C, while an independent laboratory (Cumberland Valley Analytical Services Inc., Hagerstown, MD) was used to conduct chemical analysis for nutrient composition. Metabolizable energy concentration was estimated using the Large Ruminant Nutrition System (http://nutritionmodels.tamu.edu/lrns.htm) which is based on the Cornell Net Carbohydrate and Protein System.

Growth rates of individual steers were calculated by linear regression of serial BW on day of trial using the PROC GLM procedure of SAS, and the regression coefficients used to compute ADG, and mid-test $BW^{0.75}$ (Jackson et al., 2016). Moisture analysis from weekly samples were used to adjust feed intake measurements to determine daily DMI. Estimates for missing feed intake data were derived from linear regression of the feed intake on the day of trial as described in Hebart et al. (2004).

Residual feed intake was calculated as the difference between expected and actual DMI from linear regression of DMI on ADG and mid-test $BW^{0.75}$ (Koch et al., 1963), with year and pen within year included as fixed affects. Similarly, residual gain (**RG**) was computed as the residual from the linear regression of ADG on mean DMI and mid-test $BW^{0.75}$ with fixed effects of year and pen within year (Koch et al., 1963). Within trial, steers were ranked by RFI and classified into one of three RFI phenotypic groups; low (< 0.5 SD), medium (± 0.5 SD) or high (> 0.5 SD). To examine the differences of performance, feed efficiency, and feeding behavior traits among RFI classes, a mixed model (SAS Inst. Inc., Cary, NC) that included fixed effect of RFI classification, and random effects of year and pen within year was used. Tukey-Kramer *post-hoc* test was used to evaluate differences among treatment means. The PROC CORR procedure of SAS (SAS Inst. Inc., Cary, NC) was used to determine phenotypic correlation coefficients among FB and performance traits.

Partial Least Squares Regression Analysis

The PLS method was used to develop predictive equations for DMI and feed efficiency traits (RFI, RG) that included FB traits, with and without carcass ultrasound traits, as independent variables. Two validation methods (leave-one-out cross validation and test-set validation) were used to evaluate the accuracy of the prediction equations. Leave-one-out cross-validation was accomplished by iteratively removing one animal at a time from the database and predicting the removed observation's value based on the remaining observations in the dataset. Test-set validation was accomplished by selecting either a trial or a pen to serve as the validation group, and either the remaining 2 trials or the remaining pen were used to develop a calibration equation, which was used to predict the independent variable in the remaining group.

The accuracy of the PLS models were evaluated based on: (1) standard errors of calibration (**SEC**), validation (**SEV**), and cross-verification (**SECV**), (2) coefficients of determination for calibration (**R^2C**), validation (**R^2V**), and cross-verification (**R^2CV**), and (3) mean bias. Spearmans rank correlations between predicted and actual feed efficiency values were utilized to test the re-ranking of animals (Gomes et al., 2012). The mean squared error of prediction (**MSEP**), mean bias (**MB**), model accuracy (**CB**), and concordance correlation coefficient (**CCC**) were computed to assess the precision and accuracy of the PLS models. The PLS model was selected to reduce the standard error and MSEP while maximizing the R^2 value and retain as many variables in the model as necessary to create useful prediction equations.

To further evaluate the ability of the PLS model to predict RFI, animals were classified into RFI phenotype groups, firstly based upon their actual RFI and secondly by their predicted RFI. Individuals were subsequently classified as either 1) re-ranking from High to Low RFI, 2) re-ranking from Low to High RFI, 3) the difference between actual and predicted RFI classification differed by a single class (e.g., High to Medium; Medium to Low), or 4) the animal's classification did not change between predicted and actual RFI rankings. Mean separation using Tukey Separation in PROC Mixed model SAS (SAS Inst. Inc., Cary, NC) was used to differentiate among the means of animals that were re-ranked to identify key phenotypical and behavioral traits indicative of animals that differ in their actual and predicted RFI classifications.

The PLS regression method was used to develop predictive equations for DMI using FB and growth traits, with and without carcass ultrasound traits, as the independent variables. Two validation methods were considered when evaluating these DMI-prediction models. Furthermore, G:F was calculated using predicted DMI from the model developed using the leave-one-out cross-validation method.

Results and Discussion

Summary statistics for performance, feed efficiency, ultrasound and feeding behavior traits are presented in Table 3.3 and Table 3.4. The initial age of steers at the start of the trials averaged 290 ± 16 d and ranged from 280 to 313 d. The regression model used to compute RFI, revealed that ADG and mid-test $BW^{0.75}$ accounted for 45.5% of the variation in DMI. St-Pierre (2001) indicated that ignoring the effect of trial by independent variable interactions when performing regressions across multiple trials would lead to possible biased estimates of regression coefficients, thereby resulting in biased estimates of the residual variance. Means and SD for RG and RFI were 0.00 ± 0.19 kg/d and 0.00 ± 0.78 kg/d, with RG ranging from -0.55 to 0.57 kg/d and RFI ranging from -3.38 to 2.30 kg/d, respectively. Performance, feed efficiency, and ultrasound traits for composite Angus steers with divergent RFI are presented in Table 3.3. Feed-efficient cattle consumed 16.0% less DMI, and 16.5% less DMI as percent of BW, while initial hip height, initial BW, and ADG were not different compared to high-RFI steers. Low-RFI steers exhibited greater RG compared to inefficient steers, and feed-efficient steers had less ($P < 0.05$) initial and final BF depth and less final IMF compared to high-RFI steers. However, initial IMF and initial LM area did not differ ($P > 0.14$) among steers in divergent RFI classes.

Consistently Efficient: Feeding Behavior Differences Among Feed Efficiency Classes of Beef Cattle

Previous research has illustrated that cattle with divergent RFI phenotypes express distinctive FB patterns. Feeding behavior traits for composite Angus steers with divergent RFI are presented in Table 3.4 and phenotypic correlations among feeding behavior, performance and feed efficiency traits are reported in Table 3.6. Thirteen FB traits significantly correlated ($P < 0.05$) with RFI in a positive manner. Compared to high-RFI steers, low-RFI steers had 18% fewer ($P < 0.01$) BV events and 11% fewer ($P < 0.01$) meal events. Fitzsimons et al. (2014) reported a 24% reduction in BV frequency in low-RFI dairy cows, which is in agreement with the 39% reduction reported by Nkrumah et al. (2006) in feed efficient Angus and Charolais bulls. Durunna et al. (2011b) reported a 13% reduction in BV frequency for low-RFI crossbred steers compared to their inefficient counterparts. In contrast, Kayser et al. (2013) reported no difference in BV frequency among RFI groups in both Hereford and Angus bulls, which is supported by results reported by Lancaster et al. (2009) in Angus bulls and by Hafla et al. (2013) in Bonsmara heifers.

The association between the duration of BV and meal events, and RFI have been more consistent. In the current study, low-RFI steers had a 23.5% reduction ($P < 0.01$) in BV duration, and a 36% lower ($P < 0.01$) HD duration compared to high-RFI animals. Nkrumah et al. (2006) found that feed efficient bulls visited the bunk 35% less than the high-RFI group, while Durunna et al. (2011b) concluded that finishing crossbred steers spent 19% less time visiting the feed bunk. Kayser et al. (2013) reported a 31% reduction in HD duration for both low-RFI Hereford and Angus bulls, which is in agreement with Lancaster et al. (2009), who found a 15.4% decrease in HD duration and 13.0% reduction in BV duration between feed-efficient vs. inefficient bulls. Breaking with the norm, Bingham et al. (2009) reported that low-RFI Brangus heifers exhibited 18.5% greater HD duration compared to the high-RFI group, which is in disagreement with current findings. However, Bingham collected his FB via time-lapse video and video observers for intermittent intervals throughout the study, so HD duration may not be the same trait measured by the GrowSafe® system.

Efficient steers (low-RFI) took, 10 min longer ($P < 0.01$) on average to approach the bunk following feed delivery compared to inefficient steers. There was a tendency ($P = 0.07$) for meal criterion to be longer in low-RFI compared to high-RFI steers, which is similar values calculated by Hafla et al. (2013) in Brangus heifers. Meal duration was weakly associated with RFI (0.26) and DMI (0.16), such that low-RFI animals had 13% shorter meal duration compared to high RFI animals. Average meal lengths between low-RFI and high-RFI steers did not differ. Furthermore, feed efficient steers had 48% fewer BV events per meal, spent 16.8% less time in HD duration per BV duration, and had a 26.2% shorter HD duration per meal duration when compared to high-RFI steers.

Compared to high-RFI steers, feed efficient animals exhibited significantly less ($P < 0.01$) day-to-day variation in DMI and FB patterns. Day-to-day variation in DMI was 9.7% lower in feed efficient steers, with a corresponding reduction of 23.5 and 13.8% in BV frequency and duration respectively. When considering HD duration, low-RFI steers spent 36% less time with their head in the bunk compared to less efficient animals. Like

BV traits, day-to-day variation for meal frequency and duration was 12.5% less ($P < 0.01$) for low-RFI steers. In contrast, low-RFI steers had greater day-to-day variation in both TTB and maximal non-feeding interval. In stark contrast, no differences between RFI cohorts were found for either meal length or the variation in meal length ($P > 0.14$). Little data is reported in the literature to describe this phenomenon. However, erratic FB and variation in daily DMI is commonly associated with sub-clinical acidosis and reduced performance by nutritionist and cattle feeding managers. Sub-clinical acidosis has been linked to reduced performance by Galyean et al. (1995), who demonstrated that artificially produced intake variation decreased animal gain and feed efficiency (Stock et al., 1995). Also, introduction of monensin into the diet reduces variation in DMI, and results in reduced incidence of digestive disorders (Black and McQuilken, 1980; Cooper et al., 1997). In addition to the alteration of digestion, this change in FB patterns is attributed to improved performance.

Devries et al. (2009) reports that dairy heifers facing increased bunk competition to access feed offered ad libitum in Insentec® feed bunks exhibit increased variation in day-to-day variation in feeding patterns. But despite increased competition, no changes were observed in mean or day-to-day variation of DMI. Moreover, Hosseignkhani et al. (2008) found that though eating rate was increased while BV duration was reduced due to increased competition, the degree of feed sorting remained the same. The combination of increased day-to-day variation in both DMI and FB associated with feed efficiency in the current study suggests that bunk competition may not be the cause.

These values indicate a distinctive pattern arising between low-RFI and high-RFI steers. Low-RFI steers were more reticent in their approach to the bunk, had fewer BV and meal events per day that were shorter in length. The reduction in day-to-day variation of the FB between steers from divergent RFI groups indicates that feed efficient animals are more consistent in their feeding patterns.

Partial Least Squares Regression

Partial least squares regression was used to analyze the variation explained in DMI, RFI, and RG using independent variables of feeding behavior or feeding behavior combined with ultrasound traits. Finally, the selected variables were used to create a prediction equation for DMI, RFI, or RG. For each PLS model, the optimal number of latent factors to be retained was determined by comparing the root mean of the predictive residual sum of squares (**PRESS**) using leave-one-out cross-validation.

As an example, the factor selection for RFI predicted using only FB are presented in Table 3.8. The table details the percent variation accounted for by the factor in both the independent and dependent variables. The minimum PRESS value occurred at factor 9, with a value of 0.841. Thus, 9 latent factors explaining 99.7 and 42.1% of the variation in the independent (FB) and dependent (RFI) traits, respectively, were used in the PLS model to create a prediction equation for RFI.

Predicting RFI, DMI, and RG with Feeding Behavior Traits

Based on Wold's criterion, (Wold et al., 2001), independent variables with VIP scores greater than 0.8 were retained in the final model. Standardized regression coefficients and VIP scores generated by the PLS model to predict RFI based on FB and FB combined with ultrasound traits are presented in Table 3.9. Nine FB traits explaining 42.1% of the variation in RFI were selected by the PLS regression method. The PLS model retained BV frequency and duration, HD duration, and the day-to-day variation of these traits, as well as meal duration and ratio traits HD duration per BV duration and HD duration per meal duration. Inclusion of ultrasound traits in combination with FB traits explained 46% of the variation in RFI, which included the 9 feeding behavior traits listed above in addition to initial backfat depth and gain in backfat depth. A comparison of model fit statistics between the feeding behavior and feeding behavior combined with ultrasound traits indicates only a slight improvement with the additional variables. Standard error of cross-validation reduced from 0.60 to 0.57 by including ultrasound traits, while the MSEP and Mean Bias were reduced by 0.03 and 0.02, respectively. The Spearmans rank correlation between observed and predicted values improved from 0.59 to 0.63 with the addition of initial backfat depth and gain in backfat depth. Lancaster et al. (2009) used stepwise regression analysis and reported that gain backfat depth and final longissimus muscle area explained 9% of the variation in DMI in Brangus heifers. However, the increase seen in the current PLS model falls in line with values presented by Basarab et al. (2003), and Herd et al. (2003) who reported that the inclusion of carcass traits increased the R^2 from 2 to 4 percentage points for linear regression models predicting DMI.

The least squares means for steers categorized based on actual and predicted RFI phenotype groups are presented in Table 3.11, while the percentage of steers falling into each category, (Correct Class, low-RFI to high-RFI, high-RFI to low-RFI, or One class change), are presented in Table 3.12. Results showed that both PLS models using either feeding behavior or feeding behavior combined with ultrasound correctly assigned 57% of steers to the correct RFI class. Alternatively, only 5% of steers were predicted in the most divergent class from that observed; 2.5% were observed to be low-RFI, but predicted to be high, with the remaining 2.5% observed in the high-RFI group but classified as low-RFI with the PLS model. A mean separation test among the categories (presented in Table 3.11), found no significant (*P* > 0.14) differences, with the exception of BV duration, and HD duration (*P* < 0.01). Cattle whose feeding behavior pattern for these two traits did not follow that expected for low and high RFI animals were incorrectly classified by the model. This further demonstrates the importance of these to traits that not only had the highest correlation with RFI (0.52 and 0.56, respectively), but also both returned the highest VIP values of 1.30.

The same approach described above was used to generate PLS prediction equations for both DMI and RG. For DMI and RG, 7 and 3 factors were retained for each model, respectively. Partial least squares regression identified 12 feeding behavior traits to explain 28% of the variation in DMI, and 9 feeding behavior traits that explained only 8% of the variation in RG. The model predicting DMI selected BV frequency and duration, HD duration, TTB, and meal duration, the day-to-day variation for these traits and the ratio of HD duration per BV duration, HD duration per meal duration, and BV per meal. Partial least squares regression selected BV duration, HD duration, TTB, and the day-to-day variation of these traits, as well as meal duration and ratio traits HD duration per BV duration and HD duration per meal duration. These values highlight the importance of duration traits as they relate to both DMI and feed efficiency, and it is obvious that these traits will serve as focal points for any model utilizing feeding behavior as a bio-marker in a selection index.

Combining feeding behavior with ultrasound traits drastically improved the variation explained in DMI. The PLS model selected 8 feeding behavior and 8 ultrasound traits, which explained 44% of the variation in DMI. The traits selected were BV duration, HD duration, meal duration, the day-to-day variation in these traits, and the three ratio traits HD d duration per BV duration, HD duration per meal duration, and BV per meal, which were combined with all ultrasound variables with the expectation of initial IMF. Model fit was drastically improved compared to the model created using feeding behavior only. The SECV decreased from 0.91 to 0.79, with a corresponding decrease in Mean Bias and MSEP from 0.73 to 0.64 and 0.82 to 0.63, respectively. An increase in the CCC from 0.43 to 0.61 indicated a better model fit, as well as a 15% improvement in the Spearmans rank correlation statistic. Inclusion of ultrasound traits in the PLS regression model predicting RG increased the percent of variation explained from 8 to 13% by retaining the same 9 feeding behavior traits in addition to initial backfat, initial IMF, and initial and gain in LM area. Model fit statistics for the 2 models predicting RG were the poorest among all three independent variables. The original model developed using only feeding behavior traits had an SECV of 0.17. Addition of ultrasound traits reduced the SECV to 0.16, and both models had identical Mean Bias, and MSEP values of 0.13 and 0.03, respectively. Inclusion of ultrasound traits increased the CCC from 0.15 to 0.23, and the Spearmans rank correlation statistic from 0.26 to 0.35, for the feeding behavior and the feeding behavior combined with ultrasound models, respectively.

Predicting DMI with PLS Regression using BW, Growth, and Feeding Behavior Traits

Feeding behavior was combined with BW and ADG to predict DMI using PLS regression. The model selected 11 feeding behavior traits that in combination with ADG and BW explained 67% of the variation in DMI, which is significantly improved compared to the linear regression model containing BW and ADG alone which only explained 45.5%

of the variation in RFI. Addition of feeding behavior combined with ultrasound traits explained 71% of the variation in DMI when used in PLS regression in conjunction with ADG and BW. The model fit statistics are presented in Table 3.14, and a moderate reduction in SECV is noted with the inclusion of ultrasound traits from 0.61 to 0.58, and in Mean Bias from 0.49 to 0.46. Only a slight increase was noted in both CCC and Spearmans rank correlation after the addition of ultrasound traits to the model.

This indicates the opportunity to avoid issues associated with collinearity in feeding behavior traits which limits their use in multiple linear regression equations. However, the explained variation from both the PLS and linear regression model are less than that reported in the literature. Durunna et al. (2009b) reported that BW, ADG, and initial backfat depth explained 59 and 54% of the variation in DMI during the growing and finishing phase for crossbred steers. Stepwise regression was used to include the feeding behavior traits of BV frequency and duration, and HD duration, which increased the explained variation to 66 and 68% for the growing and finishing phase respectively (Durunna et al., 2009b). However, the linear regression model explained less variation in DMI than reported by Lancaster et al. (2009), Durunna et al. (2011a), and Durunna et al. (2012), indicating that the increase in variation explained by feeding behavior is greater than that reported in the literature. This indicates the power of PLS regression to increase the accuracy of a model by accurately accounting for the collinearity among feeding behavior traits.

Multiple papers have reported an improvement in explained variation in RFI by inclusion of feeding behaviors in the model. Durunna et al. (2011b) reported a 14% increase in explained variation in RFI by including feeding behavior traits BV frequency and duration, and HD duration in addition to BW and ADG in finishing steers. Kayser et al. (2013) found that HD duration explained between 18 and 35% of the variation in DMI in Angus and Hereford bulls, respectively.

Implications

Technology improvements have made it cost effective to measure feed intake and feeding behavior (Kayser et al., 2013), however, the prohibitive cost of the equipment has reduced the number of replacement animals who are directly selected for feed efficiency. With the development of new technology capable of reporting individual animal behavior, the ability to indirectly predict an animal's efficiency classification relative to other animals in the cohort may be possible. In the current study, animals in the low RFI class exhibited lower DMI, and improved G:F without compromising growth measures of performance. By using feeding behavior traits, it was possible to account for a moderate percentage of the variation in DMI and RFI, while only incorrectly classifying 5% of the animals into an RFI class greater than 2 from that originally observed. Moreover, the combination of easily measured BW and growth traits with feeding behavior traits improved the prediction of DMI to a greater degree from that expected in the literature using multiple linear regression. Thus, it is a safe conclusion that PLS offers the ability to accurately identify feed efficient animals as well improve the accuracy of predicting DMI when combined with growth and BW.

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Tables

Table 3.1 Ingredient and chemical composition of experimental diets.

Item	Year 1	Year 2	Year 3
Ingredient composition, % as-fed			
Dry rolled corn	72.7	73.7	74.28
Brome hay	5.5	6.0	5.44
Cottonseed meal	8	6.0	7.82
Cottonseed hulls	5.5	6.0	5.44
Molasses	5	5.0	6.05
Mineral premix[1]	2.5	2.5	0.23
Urea	0.8	0.8	0.73
Chemical analysis, % DM			
DM, %	88	90.2	88
CP, %	11	12.6	14.9
NDF, %	17.9	20.3	20.8
ME, Mcal/kg	2.75	2.71	2.60

[1]Mineral premix contained minimum 15.5% Ca, 2800 ppm Zn, 1200 ppm Mn, 12 ppm Se, 14 ppm Co, 30 ppm I, 45.4 KIU/kg Vit-A, 2.3 KIU/kg Vit-D, 726 IU/kg Vit-E, 1200 Monensin, and 400 ppm Tylan.

Table 3.2 Definitions of feeding behavior traits.

Item	Definition
Bunk Visit (**BV**) frequency, events/d	Number of BV events recorded each day
BV frequency SD[1], events/d	Day-to-day variation in BV events recorded each day
BV duration, min/d	Sum of the length of all BV events recorded each day
BV duration SD[1], min/d	Day-to-day variation of the sum of the length of all BV events recorded each day.
Head down (**HD**) duration, min/d	Number of EID recordings each day multiplied by the scan rate of the of GrowSafe system
HD duration SD[1], min/d	Day-to-day variation in HD duration for each animal
Time to bunk, min	Length of interval between feed-delivery and the first BV event following feed delivery each day
Time to bunk SD[1], min	Day-to-day variation in Time to bunk for each animal
Meal frequency, events/d	Number of meal events recorded each day
Meal frequency SD[1], events/d	Day-to-day variation in the meal frequency for each animal
Meal duration, min/d	Sum of the duration of each meal event recorded each day
Meal duration SD[1], min/d	Day-to-day variation in meal duration for each animal across the trial period
Max non-feeding interval	The maximum amount of time between BV for each animal every day.
HD duration per meal duration	Ratio of HD duration to meal duration
HD duration per BV duration	Ration of HD duration to BV duration
BV events per meal event	Ratio of the number of BV recorded per meal
Meal criterion, min	Maximum time interval between bunk visits used to group BV into meals. Calculated using a Normal-Weibull distribution on the feeding non-feeding interval for each animal

[1]SD = Day-to-day variation.

Table 3.3 Performance, feed intake, feed efficiency and ultrasound traits for composite Angus steers with divergent residual feed intake phenotypes.

Item	Mean	SD	Low RFI[1]	Medium RFI[1]	High RFI[1]	SE	P - value
No. of steers	508	--	146	210	152	--	--
Performance and feed efficiency traits							
Initial BW, kg	309.3	56.5	310.8	308.0	309.8	22.1	0.62
ADG, kg/d	1.71	0.27	1.71	1.71	1.71	0.73	0.99
Mid-test BW, kg $^{0.75}$	84.1	9.1	84.3	83.9	84.0	3.4	0.71
DMI, kg/d	10.11	1.07	9.23[a]	10.09[b]	10.99[c]	0.12	< 0.01
DMI, % BW	2.77	0.34	2.52[a]	2.77[b]	3.02[c]	0.11	< 0.01
DMI SD, kg/d	2.39	0.41	2.28[a]	2.37[b]	2.53[c]	0.78	< 0.01
RFI[1], kg/d	0.000	0.784	-0.898[a]	0.006[b]	0.870[c]	0.044	< 0.01
RG[2], kg/d	0.000	0.178	0.054[a]	0.004[b]	-0.057[c]	0.014	< 0.01
G:F	0.170	0.027	0.186[a]	0.170[b]	0.156[c]	0.009	< 0.01
Initial hip height, cm	110	63	103	118	105	9	0.38
Ultrasound traits							
Initial BF[3] depth, cm	0.154	0.075	0.153[a]	0.166[b]	0.160[b]	0.028	0.05
Final BF[3] depth, cm	0.282	0.092	0.255[a]	0.289[b]	0.299[b]	0.022	0.01
Initial IMF[4], %	2.84	0.62	2.87	2.82	2.85	0.17	0.67
Final IMF[4], %	3.15	0.70	3.03[a]	3.16[ab]	3.24[b]	0.15	0.02
Initial LM area, cm^2	8.04	1.11	8.13[a]	8.05[b]	7.94[b]	0.34	0.14
Final LM area, cm^2	10.21	1.19	10.37[a]	10.14[b]	10.14[b]	0.25	0.09

[1]RFI = residual feed intake; [2]RG = residual gain; [3]BF = 12th-rib fat depth; [4]IMF = intramuscular fat. [a,b,c]Means with different superscripts differ at $P < 0.05$.

Table 3.4 Feeding behavior traits for composite Angus steers with divergent residual feed intake (RFI) phenotypes.

Item	Mean	SD	Low RFI	Medium RFI	High RFI	SE	P - Value
No. of steers	508	--	146	210	152	--	--
*Bunk visit (**BV**) traits*							
Bunk visit (**BV**) frequency, events/d	48.4	12.8	43.5^{a}	48.7^{b}	52.8^{c}	3.9	< 0.01
BV frequency SD[2], events/d	16.23	4.92	14.88^{a}	16.34^{b}	17.37^{c}	1.07	< 0.01
BV duration, min/d	62.5	13.0	54.5^{a}	61.8^{b}	71.3^{c}	1.9	< 0.01
BV duration SD[2], min/d	18.92	3.97	17.50^{a}	18.89^{b}	20.30^{c}	0.62	< 0.01
Head down (**HD**) duration, min/d	44.6	14.0	35.4^{a}	43.4^{b}	55.1^{c}	0.8	< 0.01
HD duration SD[2], min/d	14.09	4.14	12.09^{a}	13.90^{b}	16.27^{c}	0.47	< 0.01
Time to bunk, min	88.0	37.1	96.1^{a}	87.0^{b}	86.0^{b}	10.2	< 0.01
Time to bunk SD[2], min	109.9	31.2	115.8^{a}	109.2^{b}	108.2^{b}	3.2	< 0.05
Meal traits							
Meal criterion, min	13.1	8.6	14.4^{a}	12.6^{b}	12.5^{b}	1.6	0.07
Meal frequency, events/d	6.03	2.50	5.55^{a}	6.22^{b}	6.24^{b}	0.53	< 0.01
Meal frequency SD[2], events/d	2.10	1.08	1.89^{a}	2.21^{b}	2.16^{b}	0.21	< 0.01
Meal duration, min/d	123.9	25.5	115.9^{a}	122.8^{b}	133.2^{c}	3.7	< 0.01
Meal duration SD[2], min/d	60.32	16.53	56.93^{a}	59.31^{b}	65.00^{c}	2.39	< 0.01
Meal length, min/event	25.2	12.2	25.1	25.3	27.2	2.1	0.14
Meal length SD[2], min/event	9.19	4.78	9.15	9.30	9.47	0.72	0.80
Max non-feeding interval, min	663.42	77.45	670.86^{a}	666.86^{a}	652.56^{b}	18.26	0.04
Max non-feeding interval SD[2], min	231.0	61.5	295.1^{a}	292.9^{b}	285.5^{c}	16.7	< 0.01
Ratio traits							
HD duration per BV duration	0.720	0.112	0.640^{a}	0.700^{b}	0.770^{c}	0.020	< 0.01
HD duration per meal duration	0.366	0.111	0.310^{a}	0.360^{b}	0.420^{c}	0.014	< 0.01
BV events per meal event	8.74	2.84	8.25^{a}	8.66^{ab}	9.31^{b}	0.01	< 0.01

[2]SD = day to day variation.

Table 3.5 Phenotypic correlations between performance, feed intake, and feed efficiency traits in composite Angus steers (N = 508).

Item	ADG	DMI	G:F	RG[1]	RFI[2]	RFIc[3]
Initial BW	-0.38*	0.44*	-0.64*	-0.11*	-0.01	-0.01
ADG		0.28*	0.77*	0.66*	0.00	0.00
DMI			-0.38*	0.00	0.74*	0.70*
G:F				0.63*	-0.49*	-0.47*
RG[1]					-0.30*	0.29*
RFI[2]						0.96*

[1]RG = residual gain; [2]RFI = residual feed intake; [3]RFIc = residual feed intake adjusted for composition; [4]MBW = mid-test BW; * Correlations are different from zero at P < 0.05.

Table 3.6 Pearson correlations between performance and feed efficiency and feeding behavior traits in composite Angus steers.

Item	Initial BW	ADG	DMI	DMI SD[3]	G:F	RG[1]	RFI[2]
Bunk visit (**BV**) frequency	0.40*	-0.40*	0.23*	0.35*	-0.52*	-0.01	0.27*
BV frequency SD[3]	0.18*	-0.33*	0.23*	0.42*	-0.38*	-0.08	-0.21*
BV duration	-0.23*	0.22*	0.35	0.05	-0.03	-0.06	0.52*
BV duration SD[3]	0.18*	-0.22*	0.16*	0.50	-0.32	-0.09	0.25*
Head down (**HD**) duration	-0.06	0.05	0.40*	0.19*	-0.22*	-0.09	0.56*
HD duration SD[3]	0.08	-0.16*	0.24*	0.44*	-0.31*	-0.12*	0.38*
Time to bunk	-0.37*	0.15*	-0.21*	-0.08	0.26*	-0.17*	-0.10*
Time to bunk SD[3]	-0.09*	0.01	-0.15*	-0.02	0.11*	-0.04	-0.14*
Meal criterion	-0.20*	0.35*	-0.02	-0.05	0.34*	0.13*	-0.10*
Meal frequency	0.15*	-0.23*	0.05	0.13*	-0.24*	0.01	0.08
Meal frequency SD[3]	0.02	-0.13*	0.03	0.06	-0.14*	0.01	0.10*
Meal duration	-0.22*	0.24*	0.16*	0.02	0.12*	0.08	0.25*
Meal duration SD[3]	0.04	0.02	0.16*	0.15*	-0.09*	-0.00	0.17*
Max non-feeding interval	-0.28*	0.02	-0.16*	-0.04	0.12*	-0.15*	-0.08
HD duration per meal duration	0.10*	-0.12*	0.31*	0.20*	-0.32*	-0.15*	0.40*
HD duration per BV duration	0.18*	-0.21*	0.33*	0.29*	-0.41*	-0.11*	0.42*
BV events per meal event	0.17*	-0.08	0.15*	0.19*	-0.17*	-0.04	0.14*

[1]RG = residual gain; [2]RFI = residual feed intake; [3]SD = Day-to-day variation; * Correlations are different from zero at $P < 0.05$.

Table 3.7 Pearson correlations between feeding behavior traits in composite Angus steers.

Item	BV frequency SD[1]	BV duration	BV duration SD[1]	HD duration	HD duration SD[1]	Time to bunk	Time to bunk SD[1]	Meal frequency	Meal frequency SD[1]	Meal duration	Meal duration SD[1]	Meal Criterion
Bunk visit (**BV**) frequency	0.73*	0.00	0.40*	0.19*	0.32*	-0.53*	-0.30*	0.46*	0.36*	0.20*	0.25*	-0.38*
BV frequency SD[1]		0.04	0.46*	0.17*	0.40*	-0.24*	-0.14*	0.33*	0.28*	0.13*	0.27*	-0.29*
BV duration			0.51*	0.87*	0.66*	0.11*	-0.04	-0.04	0.03	0.46*	0.27*	0.06*
BV duration SD[1]				0.51*	0.85*	-0.07	0.01	0.09	0.04	0.30*	0.30*	-0.09
Head down (**HD**) duration					0.78*	0.01	-0.05	0.07	0.10	0.37*	0.27*	-0.02
HD duration SD[1]						0.01	0.03	0.09	0.08	0.28*	0.27*	-0.08
Time to bunk							0.59*	-0.37*	-0.32*	-0.08	-0.17*	0.24*
Time to bunk SD[1]								-0.29*	-0.33*	-0.15*	-0.20*	0.15*
Meal frequency									0.94*	-0.41*	-0.29*	-0.66*
Meal frequency SD[1]										-0.36*	-0.25*	-0.63*
Meal duration											0.74*	0.60*
Meal duration SD[1]												0.47*

[1]SD = Day to day variation.

Table 3.8 Proportion of variation accounted for by feeding behavior or residual feed intake using partial least squares regression with the leave-one-out cross-validation method.

Number of extracted components	Percent variation accounted for				Cross-validation	
	Independent variables		Dependent variable		Root mean	Comparison
	Current	Total	Current	Total	PRESS[1]	P - Value
0	0.000000	0.000000	0.000000	0.000000	1.079774	<0.01
1	0.489762	0.489762	0.310098	0.310098	0.902203	<0.01
2	0.099073	0.588835	0.060425	0.370523	0.869453	<0.05
3	0.134799	0.723634	0.011246	0.381768	0.860052	0.12
4	0.088979	0.812613	0.005386	0.387154	0.857659	0.16
5	0.124108	0.936721	0.001898	0.389052	0.856477	0.22
6	0.046488	0.983210	0.006078	0.395130	0.856714	0.17
7	0.010214	0.993423	0.016971	0.412100	0.850523	0.11
8	0.004148	0.997572	0.006263	0.418363	0.844679	0.20
9	0.002428	1.000000	0.002669	0.421032	0.841316	1.00

[1]PRESS = predictive residual sum of squares.

Table 3.9 Coefficient and variable of importance values for leave-one-out cross-validation method using feeding behavior to predict residual feed intake in composite Angus steers.

	Feeding behavior only		Feeding behavior plus Ultrasound	
Variable	Coefficient	VIP[2] score	Coefficient	VIP[2] score
Bunk visit (**BV**) frequency	0.25	0.80	0.23	0.81
BV frequency SD[1]	0.06	0.72	0.08	0.71
BV duration	1.50	1.30	1.39	1.32
BV duration SD[1]	-0.12	0.96	-0.08	0.95
HD duration	-1.18	1.30	-1.15	1.37
HD duration SD[1]	-0.14	1.08	-0.18	1.11
Meal duration	-0.15	0.70	-0.11	0.70
HD per meal duration	-0.19	0.93	-0.16	1.00
HD duration per BV duration	0.95	1.00	1.00	1.05
Initial BF depth	--	--	0.03	0.75
BF depth gain	--	--	0.20	0.96

[1]SD = Day to day variation; [2]VIP = Variable of importance to projections.

Table 3.10 Summary statistics for the leave-one-out cross-validation prediction PLS models used to predict DMI, RFI, and RG using feeding behavior and feeding behavior combined with ultrasound traits in composite Angus steers.

	Cross Validation						
Model	N	SECV[3]	R^2CV[4]	Mean Bias[5]	CCC[7]	MSEP[8]	Spearmans[6]
Feeding behavior only							
Dry matter intake	508	0.91	0.28	0.73	0.43	0.82	0.49
Residual feed intake	508	0.60	0.42	0.48	0.59	0.36	0.59
Residual gain	508	0.17	0.08	0.13	0.15	0.03	0.26
Feeding behavior plus ultrasound							
Dry matter intake	508	0.79	0.44	0.64	0.61	0.63	0.64
Residual feed intake	508	0.57	0.46	0.46	0.63	0.33	0.63
Residual gain	508	0.16	0.13	0.13	0.23	0.03	0.35

[1]SEC = standard error of validation; [2]R^2C = coefficient of determination for calibration; [3]SECV = standard error of cross-validation; [4]R^2CV = coefficient of determination for cross-validation; [5]Mean Bias = absolute mean difference between observed and predicted RFI; [6]Spearmans = Spearmans rank correlation between observed and predicted values; [7]CCC = concordance correlation coefficient (higher better); [8]MSEP = mean squared error of prediction.

Table 3.11 Least squares means for composite Angus steers that changed RFI classification between observed and predicted RFI based on feeding behavior.

Item	Low to High	No Class Change	One Class Change	High to Low	SE	P - Value
No. of steers	13	288	195	12	--	--
Performance and feed efficiency						
Initial BW, kg	307	309	309	313	23.5	0.97
ADG, kg/d	1.70	1.70	1.73	1.67	0.09	0.44
Mid-test BW, $kg^{0.75}$	83.7	83.9	84.2	84.4	3.67	0.95
DMI percent of BW	2.58	2.78	2.78	2.93	0.13	1.00
DMI, kg/d	9.37^{a}	10.10^{ab}	10.15^{b}	10.72^{b}	0.32	<0.01
RFI[1], kg/d	-0.599^{a}	0.017^{b}	-0.011^{ab}	0.376^{a}	0.209	<0.05
RG, kg/d	0.025	-0.008	0.013	-0.046	0.040	1.00
G:F	0.181^{a}	0.169^{ab}	0.171^{a}	0.155^{b}	0.011	<0.01
Bunk visit (BV) traits						
Bunk visit (**BV**) frequency, events/d	50.16	48.74	47.99	45.27	4.70	0.49
BV frequency SD[1], events/d	17.43	17.27	17.13	15.85	1.72	0.76
BV duration, min/d	73.76^{a}	62.81^{b}	61.73^{b}	56.49^{b}	3.97	0.002
BV duration SD[1], min/d	21.05	19.92	19.76	19.31	1.37	0.66
Head down (**HD**) duration, min	56.70^{a}	44.79^{b}	43.82^{b}	38.58^{b}	4.01	0.005
HD duration SD[1], min	16.67	14.92	14.88	13.69	1.32	0.36
Time to bunk, min	88.56	89.04	86.78	82.10	13.13	0.78
Time to bunk SD[1], min	107.85	111.40	108.11	104.29	10.24	0.55
Meal traits						
Meal frequency, events/d	5.84	6.01	6.08	5.91	0.82	0.97
Meal frequency SD[1], events/d	2.03	2.10	2.12	1.99	0.34	0.96
Meal duration, min/d	138.09	125.04	121.56	121.71	7.78	0.08
Meal duration SD[1], min/d	36.98	34.45	33.72	37.41	2.71	0.35
Max non-feeding interval duration, min/d	630.42	660.77	669.31	677.29	26.07	0.14
Ratio Traits						
HD duration per meal duration	0.422	0.363	0.369	0.323	0.033	0.14
HD duration per BV duration	0.767	0.701	0.705	0.673	0.037	0.17
BV events per meal event	9.55	8.81	8.61	8.18	0.85	0.54

[1]RFI = residual feed intake.

Table 3.12 Count of class switches for composite Angus steers with change in predicted RFI class using feeding behavior and the leave-one-out cross-validation technique.

Model	Low to High RFI	No Class Change	One Class Change	High to Low RFI
RG[1] FB[3]	8%	44%	43 %	5 %
RG[1] FB-US[4]	5%	44%	47 %	5 %
RFI[2] FB[3]	3%	57%	38 %	2 %
RFI[2] FB-US[4]	2%	57%	39 %	3 %

[1]RG = residual gain; [2]RFI = residual feed intake; [3]FB = feeding behavior; [4]FB-US = feeding behavior combined with ultrasound traits

Table 3.13 Coefficient and variable of importance values for the leave-one-out cross-validation method using feeding behavior to predict dry matter intake in composite Angus steers.

	Feeding behavior only		Feeding behavior plus Ultrasound	
Variable	Coefficient	VIP[2] score	Coefficient	VIP[2] score
ADG, kg/d	0.40	1.33	0.34	1.50
Mid-test BW, kg	0.70	1.66	0.71	1.52
Bunk visit (**BV**) frequency	0.18	0.65	0.24	0.96
BV frequency SD[1]	0.06	0.64	--	--
BV duration	1.07	0.88	1.01	0.95
BV duration SD[1]	-0.16	0.86	-0.09	0.88
Head down (**HD**) duration	-0.87	1.01	-0.86	1.06
HD duration SD[1]	-0.06	1.02	-0.13	0.93
Max non-feeding interval	0.14	0.73	0.15	0.78
HD duration per BV duration	0.57	0.88	0.64	0.95
HD duration per meal duration	0.02	0.86	0.02	0.89
Initial BF depth	--	--	0.22	0.85
Final BF depth	--	--	-0.27	1.09
BF depth gain	--	--	0.38	1.02
Initial IMF	--	--	-0.04	0.66
Initial LMA	--	--	-0.01	0.78
Final LMA	--	--	-0.06	0.98
Gain in LMA	--	--	0.08	0.77

[1]SD = Day to day variation; [2]VIP = Variable of importance to projections.

Table 3.14 Summary statistics for models predicting dry matter intake using mid-test BW, gain and feeding behavior traits, with and without ultrasound traits.

Item	FB	FB+
No. of steers	508	508
SECV[2]	0.61	0.58
R^2CV[4]	0.67	0.71
Mean Bias[5]	0.49	0.46
CCC[7]	0.80	0.82
MSEP[8]	0.38	0.34
Spearmans[6]	0.80	0.82

[1]SEC = standard error of validation; [2]R^2C = coefficient of determination for calibration; [3]SECV = standard error of cross-validation; [4]R^2CV = coefficient of determination for cross-validation; [5]Mean Bias = absolute mean difference between observed and predicted RFI; [6]Spearmans = Spearmans rank correlation between observed and predicted values; [7]CCC = concordance correlation coefficient (higher better); [8]MSEP = mean squared error of prediction.

Table 3.15 Summary statistics for trial by trial calibration-validation for dry matter intake using feeding behavior, body weight and gain.

Model	N	SEC[1]	R^2C[3]	N	SEV[2]	R^2V[4]	CCC[7]	MSEP[8]	Mean Bias[5]	Spearmans[6]
Dry Matter Intake										
Trial 1 and 2, predict 3	338	0.65	0.63	338	0.66	0.60	0.77	0.43	0.54	0.77
Trial 1 and 3, predict 2	340	0.60	0.67	168	0.66	0.60	0.79	0.39	0.52	0.79
Trial 2 and 3, predict 1	338	0.76	0.48	170	0.75	0.46	0.66	0.57	0.59	0.68
Pen 1, predict pen 2	253	0.58	0.70	255	0.67	0.60	0.80	0.40	0.47	0.81
Pen 2, predict pen 1	255	0.59	0.69	253	0.69	0.58	0.79	0.41	0.54	0.81

[1]SEC = standard error of calibration; [2]SEV = standard error of validation; [3]R^2C = coefficient of determination for calibration; [4]R^2CV = coefficient of determination for validation; [5]Mean Bias = absolute mean difference between observed and predicted RFI; [6]Spearmans = Spearmans rank correlation between observed and predicted values; [7]CCC = concordance correlation coefficient (higher better); [8]MSEP = mean squared error of prediction..

Figures

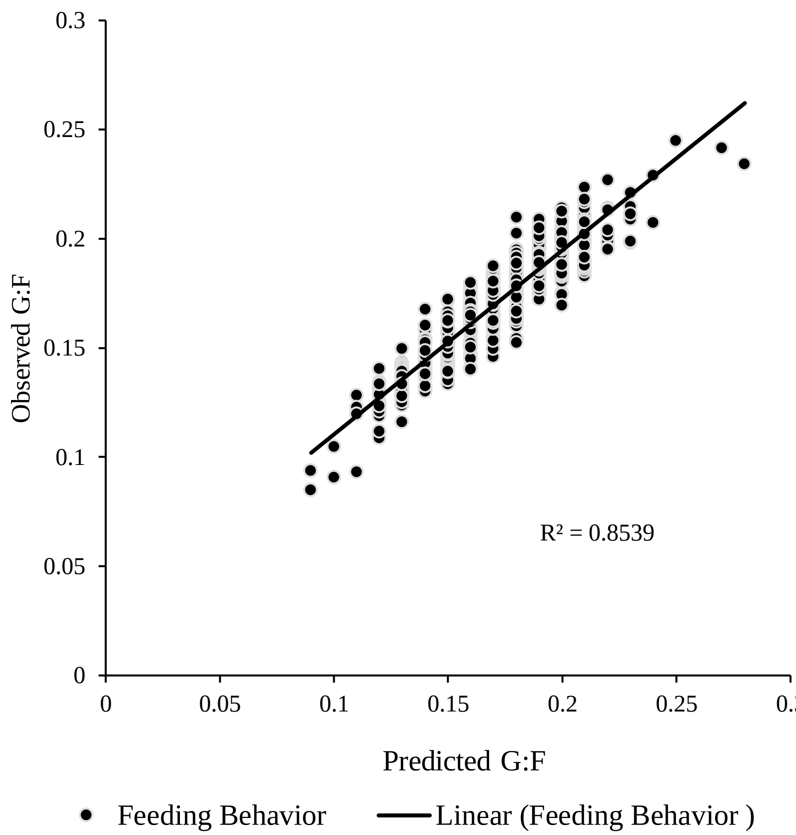

Figure 3.1 Fit between observed and predicted gain to feed calculated from dry matter intake predicted using BW, gain, and feeding behavior traits.

CHAPTER IV

CONCLUSIONS

Increasing the genetic merit of beef cattle for feed efficiency is an effective strategy to improve the economic and environmental sustainability of beef production. Residual feed intake serves as a measure of feed efficiency independent of average daily gain and body weight, where feed efficient animals consume less feed than expected. Studies have documented that divergent phenotypes for residual feed intake express distinctly different feeding behavior patterns. Chapter 2 reports the results of the validation study of a high-frequency RFID system designed to capture continuous animal behavior. The CattleTraq® system proved it can predict bunk visit frequency and duration with coefficients of determination of 0.81 and 0.88, respectively. Using the appropriate bunk visit decision rules, the system presented sensitivity and specificity values of 82% and 99%, respectively, for a combined accuracy of 90%. This meets the first objective of this research project, and as technology continues to improve, systems capable of accurately capturing continouos feeding behavior will become less expensive, creating increased interest for adoption by the livestock industry.

Results from chapter 3 demonstrated the distinctly different feeding behavior patterns expressed by cattle of divergent residual feed intake phenotypes. Feed efficient steers consumed 16% less dry matter feed intake than their high-RFI counterparts, while body weight and average daily gain were not different. Compared to high-RFI steers, low-RFI steers had 18% fewer and 24% shorter ($P < 0.01$) bunk visit events, and 11% fewer meal events that were 13% shorter ($P < 0.01$) in length. Low-RFI steers took approximately 12% more time ($P < 0.01$) to approach the bunk following feed delivery compared to inefficient animals. Farthermore, distinctive differences were found in the day-to-day variation of feeding behavior between phenotype classes for residual feed intake. Low-RFI steers exhibited 10% less ($P < 0.01$) day-to-day variation in dry matter intake, and 12 to 36% less day-to-day variance ($P < 0.01$) in head down duration, bunk visit frequency, bunk visit duration, and meal frequency and duration. This is a similar affect to that seen by the addition of monensin to diets, which has been shown to stabilize dry matter intake and feeding behavior, which is expressed in tandem with improved digestibility and feed efficiency. The similar affect expressed by feed efficient steers may indicate a natural biological mechanism which aids in improved feed efficiency, and selection for feeding behavior as a bio-marker offers promise for improving the selection of more efficient animals.

Although feeding behavior may serve as a suitable bio-marker for feed efficiency, specifically residual feed intake, the correlated nature among feeding behavior traits limits their use in multiple linear regression to create prediction equations. Partial least squares regression was used to analyze feeding behavior variables, as this method is better suited to deal with collinearty among the independent variables. Partial least squares identified 9 feeding behavior traits with variable of importance scores greater than 0.8 that explained 42% of the variation in residual feed intake. Duration traits head down duration and bunk visit duration and the day-to-day variance of these traits, were the most significant contributers to the partial least squares prediction equation based on their their coefficients and variable of importance scores. Steers were classified by the predicted residual feed intake calculated using the partial least squares prediction equation, then compared to observed residual feed intake class. The partial least squares equation correctly classified

44% of the steers, while an additional 43% were classified within one class of their observed feed efficiency class. This means that the partial least squares model correctly classified 95% of the steers within one feed efficiency class of observed using only feeding behavior traits.

Additionally, a partial least squares prediction equation created using the 9 feeding behavior traits identified previously in combination with metabolic body weight and average daily gain predicted dry matter intake with a coefficient of determination of 0.67. Using partial least squares predicted intake, the calculated gain to feed reported an 85% accuracy with observed gain to feed, indicating the opportunity to predict efficiency using in pen weighing systems in tandem with a system designed to capture continuous feeding behavior.

Continual improvement of technology will increase incorporation of feeding behavior systems in the beef industry, resulting in improved management strategies. This offers the opportunity to select for feed efficiency using feeding behavior as a bio-marker. One proposed solution to identify feed efficient animals is a two stage feeding protocol, where feeding behavior is tracked and cattle are sorted into either feed efficient or inefficient groups. Then, a second feeding period for the efficient class can be conducted, limiting the total number of cattle which must be fed in a feed intake system, such as GrowSafe®, whose initial purchase cost prohibits universal adoption by the beef industry. This strategy, or a strategy developed using strickly feeding behavior, offers the opportunity to increase the proportion of the cowherd selected for improved feed efficiency traits.