

Seedstock Bull Buying Behavior and In-store Purchasing Behavior for Value Added Cheese

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ABSTRACT

One of the important and widely common tools that bull buyers use to ease the selection process is the use of Expected Progeny Differences (EPD). This research employs a lab-in-the-field experimental design, combining real-world auction data with a survey instrument to gather insights into producers' seedstock buying behaviors using EPD information. A total of 208 participants took part voluntarily in our study; 101 of which were from Tennessee, 30 were from Alabama, 37 from West Virginia, and 40 of which were from Iowa. Each participant was randomly assigned to one of four treatments groups, which included EPD information with different arrangements. The result shows that the buyers in treatment 2 (control treatment flipped) have the highest average accuracy of predicting bull prices followed by treatment 1 (EPD values for different traits excluding percentile rank), treatment 3 (treatment 2 flipped) and control group. The findings of this study will guide breeders and industry stakeholders in developing strategies to market and promote the adoption of advanced selection tools like EPDs with its most effective layout.

The second chapter of this thesis explores consumers' preference and shopping behavior for value added local farm cheese products using eye-tracking technology in a retail setting. A total of 98 participants were recruited for the experiment with each participant incentivized \$20 for their participation that they can spend on products from the store or choose to buy nothing. In the first stage of the study, participants watched a video or read a graphical advertisement, participants walked in the store with eye tracking glasses on and made their purchases during the second stage and filled in a survey after completing their purchase. The result showed that the participants treated with the graphical image of advertising spent on average \$21.81 while those

treated with video advertising spent on average \$20.78. These results can be leveraged to understand consumer's shopping behavior in a retail outlet and provide insights for small dairy businesses moving into value addition.

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CHAPTER I

SEEDSTOCK BULL BUYING BEHAVIOR

Abstract

This study examines how different arrangements of Expected Progeny Difference (EPD) profiles influence seedstock producers' ability to accurately predict bull prices. Using a lab-in-the-field experimental design with 208 cattle producers across Tennessee, Alabama, West Virginia, and Iowa, participants were randomly assigned to one of four treatments varying the arrangements of EPD profiles. Data was collected on prediction accuracy, cognitive traits, information use, and demographic characteristics. Results show that placing economic selection indexes (\$M, \$W, \$B, \$C) at the beginning of EPD profiles significantly improves price prediction accuracy. Producers who regularly used advanced tools like Genomically Enhanced EPDs (GE-EPDs) and ranked EPDs demonstrated higher accuracy and greater ability to differentiate bull quality. Behavioral traits such as patience and trust positively influenced outcomes, while high risk tolerance and overconfidence in financial decisions were linked to lower accuracy. Producers from Iowa consistently outperformed others, highlighting regional variation. Findings suggest that optimizing EPD catalog design and promoting advanced selection tool use can enhance economic decision-making in cattle production.

Introduction

Bulls play a pivotal role in introducing new genetic attributes to a herd, making the selection of bulls with outstanding physical and genetic traits crucial (Dhuyvetter et al., 1996). Additionally, selecting the right bull is vital as it directly influences the farm's costs and revenue, thus impacting profitability (Clary et al., 1984). Therefore, producers often seek bulls with superior traits and are willing to pay a premium price for these characteristics (Kessler et al., 2017). A study by Kessler et al. (2017) using hedonic price regression analysis, showed that

producers were willing to pay premium for performance metrics like birth weight, weaning weight, and dam weight, as well as Expected Progeny Differences (EPD) such as yearling weight, milk, and stayability. EPDs serve as valuable tool for comparing the predicted genetic merit of bulls within a breed, and thus helps producers select bulls with desirable traits (Vanek et al., 2008).

Moreover, the value of EPDs lies in their ability to provide producers with data-driven insights into the genetic potential of bulls, enhancing the accuracy of selection decisions, and accelerating genetic progress. With recent technological advancements, EPDs can now include DNA profiles, enabling the development of Genetically Enhanced EPDs (GE-EPDs), helping producers make better informed decisions (Matukumalli et al., 2009; Meuwissen et al., 2001). Breed associations develop and publish EPDs in profiles for each individual animal in their respective registries. The earliest developed EPDs were for birth weight, weaning weight, yearling weight, and milk (Spangler, 2019). Since the development of these foundational EPDs, researchers and industry have developed numerous EPDs for different traits.

In the late 1990s and early 2000s, percentile ranks for EPDs began to be developed and incorporated into EPD profiles. Breed associations began releasing annual percentile breakdown tables for each trait, which listed the EPD values that correspond to each percentile threshold (e.g., 1st, 5th, 25th, 50th percentiles). These became a standard feature in bull sale catalogs, genetic evaluation reports, and online search tools (Beef Improvement Federation, 2018). So, until the early 2000s, an EPD profile displayed growth traits, reproductive traits, carcass traits, and management/convenience traits with their respective percentile rank. Starting in the early

2000s, researchers began developing and incorporating economic selection indexes into EPD profiles (American Angus Association, n.d.).

American Angus Association developed its first economic selection indexes; \$W (Weaned Calf Value) and \$B (Beef Value) in 2004. The purposes of these indexes are to estimate a single monetary numerical measure that considers multiple individual traits based on profitability. In other words, an economic selection index estimate allows for easy profitability comparison between animals of the same breed for multiple traits. Thus, these indexes make selection decisions easier and more efficient.

As economic selection indexes were being developed and adopted by American Angus Association and other breed associations, they were, and currently are, placed at the end (mostly left and/or bottom) of the EPD profile. However, research on visual attention and information design indicates that profiles are most effective when critical traits are placed at the top, as this area receives greater initial viewing and recall (Rayner, 1998). Moreover, information positioned on the left side of the profile attracts more sustained attention, while right-side elements risk being overlooked, particularly in complex layouts (Bialkova et al., 2014). These insights highlight the importance of strategic placement of economically important traits to optimize user engagement and information usage in producers' selection decision. Thus, could the current placement of economic selection indexes in the EPD profiles inhibit their usage? This research seeks to answer this question by exploring producers' preferences and prediction behaviors for different EPD profile arrangements.

Additionally, this research is unique as it employs a lab-in-the-field experimental design, combining real-world auction data with a survey instrument to gather insights into producers'

prediction behaviors. Conducted at cattle expos and bull sales, the study involves 208 participants from Tennessee, Alabama, West Virginia, and Iowa offering a diverse sample of producers. Participants were presented with various prediction tasks involving different breeds and EPD arrangements to mimic real-market scenarios. By incentivizing accurate predictions, the study aims to capture realistic decision-making patterns and preferences.

The findings of this study will provide valuable insights into how producers utilize EPDs, and the impact of different EPD arrangements on producer's price prediction for seedstock bulls. Understanding these preferences and how they impact price expectations will guide breeders, researchers, and industry stakeholders in designing EPD profiles that can help increase price expectation knowledge, and thus, better decision making. Ultimately, this research aims to enhance the beef cattle industry's efficiency and sustainability by improving the design and quality of information provided through EPD profiles which can increase economic returns. Tables and figures embedded within the chapter should be placed one of two ways: at the top or bottom of the text page (after the table/figure is referenced) if it is a single, smaller table or figure, or on a separate page following the text page where they are first mentioned. The separate page option must be used for multiple tables/figures or tables/figures that are large. The text page where the table/figure is referenced should be a full page of text, unless it is the last page of the chapter.

Literature Review

Producers look to enhance the profitability of their cattle herds by introducing seedstock bulls that possess improved genetics and traits and are often willing to pay a premium for those traits (Kessler et al., 2017). The premium payoff, or benefits, for introducing seedstock bulls

with better or more desirable physical and genetic attributes to the herd occur over time (Dhuyvetter et al., 1996). Buying a bull requires attention to the physical and genetic makeups of the individual animal, because they directly influence the cost and revenue of the farm and thus can affect profitability of the cattle operation (Clary et al., 1984). The annual genetic change rate in the seedstock sector is determined by four interrelated factors: (1) selection intensity, (2) the generation interval, which is the average age of parents at the birth of their offspring, (3) the level of genetic variation, and (4) the accuracy of selection (Van Eenennaam & Drake, 2012). Therefore, annual selection gains are maximized when a small number of the top candidates are selected and utilized extensively at a young age.

Typically, bull buyers have information about the animal's EPDs, and performance and physical traits during selection. An EPD shows the difference between the expected measurements of the bull's average offspring versus those of all other bulls in the same breed if bred to the same mates. EPD measures can be a valuable tool for producers to compare the predicted genetic merit of bulls within a breed to produce progeny with desired traits. Expected characteristics of bull's offspring are associated with EPDs, which act as proxies for offspring's characteristics (Vanek et al., 2008).

Bull EPD values are calculated based on the performance data of the individual bull, its offspring, and its relatives. When using EPDs, producers can make more accurate selection decisions and accelerate genetic progress. EPDs like expected birth weight (BW), weaning weight (WW), yearling weight (YW), milking index (Milk), intramuscular fat (IMF) and rib eye area (REA) of a bull's future progeny are commonly reported for each bull as EPD profiles (Vanek et al., 2008).

During the 2000s, studies started utilizing cattle auction data to understand how the attributes associated with bull impact producers' buying decisions. Using a hedonic analysis of U.S. beef seedstock breeds, Vanek et al. (2008) showed that buyers placed greater values on the bulls based on the expectation that their progeny would have improved traits. These expectations were guided by EPDs. For example, Dhuyvetter et al. (1996) and Chvosta et al. (2001) found that buyers often weighed actual observed traits as heavier than the associated EPDs, leaving the overall impact of EPDs inconclusive. Conversely, Jones et al. (2008) and subsequent studies reported that birth weight and carcass EPDs (e.g., ribeye area, marbling) carried significant price premiums. However, surveys by Boyer et al. (2019) suggest phenotypic traits like weight and frame score still often dominate, even as specific EPDs like ribeye area gain importance. More recent work, such as Tang et al. (2020), shows that valuations of traits like ribeye and growth-related EPDs have increased over time, although other EPDs (e.g., milk EPD) have become less influential.

Available EPDs have changed over time. With recent technological advancements, bull auction catalogs now have DNA profile information of individual bulls. The DNA information, along with other performance factors, are now incorporated into EPDs which can improve the accuracy of EPDs. The increased accuracy has great potential to improve returns in the seedstock sector (Van Eenennaam & Drake, 2012). This inclusion of genetic factors in EPDs is commonly referred by literature as Genomically Enhanced EPDs (GE-EPDs) (Matukumalli et al., 2009; Meuwissen et al., 2001). DNA information increases the accuracy of EPDs, thus allowing for a more informed selection of a bull and the associated potential genetic gain (Van Eenennaam & Drake, 2012). In fact, many seedstock producers have already started using DNA information to

verify pedigree, and to detect genetic defects in animals (Van Eenennaam et al., 2011). However, some issues arise in that the economically important traits are limited in accuracy for young animals, because some traits have low heritability. For example, reproductive traits are measurable only later in life. Moreover, longevity and carcass characteristics can be impacted by environmental conditions such as disease or nutritional stress and can only be measured later in life (Van Eenennaam & Drake, 2012). This is why the inclusion of genetic information in a bull's EPD profile becomes increasingly important for buyers to make informed decisions and make an accurate selection decision.

Vestal et al. (2013) combined actual bull sales data with a stated preference survey to understand buyer's preferences under different information treatments. They found WTP was significantly influenced by EPDs, test performance and ultrasound information while the latest DNA profile information had no effect on the buyer's preference. Van Eenennaam & Drake (2012) concluded that while combining genotyping information with EPDs information has potential for greater returns, the cost of obtaining genetic information exceeds the value that is generated by genetic information in any sector.

Smith (2021) conducted a survey in Tennessee to understand cow-calf producer's preferences for bull EPDs, and the value the producers placed on GE-EPDs. They found that, on average, producers were willing to pay \$2,293.33 for a bull with EPDs, while just \$2,282.34 for a bull with GE-EPDs, but these values were not significantly different. Given the lack of significance and potential gain through using GE-EPDs, the results suggest that the producers were not familiar with this relatively new advanced selection tool. To the contrary, Ingram et al. (2023) conducted an incentivized lab-in-the-field experiment, where producers from Tennessee

and Alabama were asked to predict the price of bulls. They found that participants utilizing GE-EPDs and EPD percentage ranks were significantly more likely to make accurate predictions, and that Tennessee producers showed higher use of genetic information than Alabama producers. These studies highlight that EPDs, and percentile rank have an impact in producers' decision-making processes.

Additionally, the concept that “what comes first is seen first” is well-established in visual cognition literature, particularly in studies of visual attention and information processing. This phenomenon, known as the primacy effect, suggests that items located at the top or beginning of a list are more likely to be noticed, remembered, and processed than those appearing later (Bundesen, 1990). In vertically arranged information displays—such as EPD profiles—this results in disproportionate visual attention and cognitive processing given to traits listed at the top of the profile. This effect is robust across different types of information displays and is especially pronounced in tasks requiring rapid scanning or decision-making (Rayner, 1998). Moreover, a recent study employing eye-tracking techniques has demonstrated that readers are more likely to skip over information on the far right, focusing instead on left and center, especially when the information is cognitively demanding or tightly packed (Bialkova et al., 2014). This leftward attentional bias is consistent across various visual tasks and is especially pronounced in Western readers, who typically scan from left to right.

These findings have important implications for the design and arrangement of information-rich displays, such as EPD profiles, as they suggest that elements positioned on the left or at the top of a vertical layout are more likely to be noticed and processed. These insights highlight the importance of strategic placement of economically important traits in EPD profiles

to optimize user engagement and information retention to make sure producers see and use important traits in their selection decision.

However, while previous research shows that producers value EPDs when selecting a bull (Boyer et al., 2019; Tang et al., 2020; Ingram et al., 2023), research is sparse with regard to explicitly testing how EPD profile arrangements and percentile rank impacts producers' accuracy of selection when buying a bull. Additionally, no research exists to understand prediction behavior of producers for selecting bull seedstock. You should not “break” text and leave white space on text pages just to show a table or figure on the next page -- instead, simply continue the text (even if it is a new paragraph or new section) until that page is filled. The only time there should be a significant amount of white space on a page is when it is the last page of the chapter. You can leave white space on pages that just have figures or tables.

Materials and Method

Data Collection

The data utilized in this study was collected at the 2023 Tennessee Cattlemen's Association annual expo, the 2023 Alabama Cattlemen's Association annual expo, the 2023 West Virginia bull sale day, and the 2024 Iowa Cattlemen's Association annual expo through incentivized lab-in-the-field experiments. At each of these events, we set up a designated research booth consisting of tables and chairs with laptops equipped with eye-tracker and online survey. This setup was located directly on the expo centers in Tennessee, Alabama and Iowa and an auction venue in West Virginia. A total of 208 participants took part voluntarily in our study; 101 of which were from Tennessee, 30 were from Alabama, 37 of which were from West Virginia, and 40 of which were from Iowa. Every respondent was compensated with \$15 for

participating in our study and had an opportunity to earn an additional \$10 reward on accurately predicting price of a randomly selected experimental task. When asked to predict the market value of the bull in each task, participants were made aware that an accurate price prediction had to be within the range of \$500 above to \$500 below the true market price. This potential additional payoff serves as an incentive for accuracy by the participants in our study (List, 2003).

At the beginning of the experiment, each participant was instructed to assume they are a buyer in the bull market and that they operate an approximately 100 cow herd on a forage-based system with little supplementation. Providing this context was intended to mimic a real cattle market scenarios and introduce consistency across the different locations and business types of participants. Participants were informed that the market prices of the bulls presented to them ranged between \$2,000 and \$8,500. This price range was provided to mirror market reports that producers often reference when making purchase decisions. While there is a possibility of anchoring bias (Tversky & Kahneman, 1974), we included this information intentionally to replicate the informational environment of actual cattle markets, where buyers rarely make decisions in the absence of market context. Providing a price range helped ensure decisions were realistic, grounded in known market dynamics, and not randomly generated in a vacuum.

We used bulls from three breeds: Angus, Simmental and Hereford sold during 2022 at seedstock bull sales in Tennessee in our study. These are among the most prevalent beef breeds in U.S. herds, particularly across Tennessee, Alabama, West Virginia, and Iowa cattle producers (Arango et al., 2002). Each participant first completed three training tasks, strategically chosen one for each breed used in the study. These were designed to mirror the structure of the main tasks and thus familiarize participants with the main tasks. Further, six bulls from each breed

were selected to form the 18 incentivized tasks in our experiment. To ensure variation in genetic potential, the six bulls from each breed were strategically selected to represent high, average, and low levels of Expected Progeny Differences (EPDs), with two bulls per EPD category. This classification ensured that participants encountered realistic and economically relevant variation in genetic merit across breeds and tasks.

Finally, participants were presented with 18 main tasks and asked to predict the market price of the bull in each task. Each task displayed a looping video (5 to 7 seconds) of a bull walking from left to right, allowing participants to visually assess phenotypic characteristics such as muscling, frame, and locomotion. The experiment was administered through an online survey interface (Qualtrics), hosted on laptops. Each task followed a consistent structure:

1. Bull video display – participants viewed looping video for visual assessment (**Figure 1**).
2. Price prediction – participants entered their estimate of the bull’s value using a fill-in-the-blank text box (e.g., "\$5,000").
3. Automated accuracy feedback – immediately after submitting a prediction for each task, the survey software informed participants whether their estimate was “accurate” or “inaccurate,” based on whether it fell within $\pm\$500$ of the bull’s actual sale price. This immediate feedback mechanism was implemented to make the task more engaging and to encourage precision in responses, as supported by incentive-compatible design principles in behavioral economics (Hertwig & Ortmann, 2001; List, 2003).



Figure 1. Screenshot From a Bull Video Provided to Participants

In addition, each participant was randomly assigned to one of three treatments groups or a control group, explained in **Figure 2**, which included EPD information of the bull in different arrangements before they were asked to predict bull's market price. The control group included EPD values for different traits along with percentile ranks of the bull for each trait compared to the breed average arranged as currently presented by breed associations. The first treatment consisted only of EPD values for different traits excluding percentile ranks. The second treatment group had all the information same as the control group, except that the traits were flipped right to left. The third treatment was similar to the second treatment but with traits flipped right to left. These EPD values for different traits of a bull were intended to establish a common baseline for all participants in their evaluations, as the bull's value might otherwise be affected by the characteristics of the respondent's herd.

Control Group		CED	BW	WW	YW	SC	HP	Milk	DOC	CW	Marb	RE	FAT	\$M	\$W	\$B	\$C
	EPD	7	3.5	70	127	1.57	11.6	28	15	62	1.0	0.72	0.024	69	62	177	299
	%			25	20	15		35		20	15	25		35	35	10	10

Treatment 1		CED	BW	WW	YW	SC	HP	Milk	DOC	CW	Marb	RE	FAT	\$M	\$W	\$B	\$C
	EPD	7	3.5	70	127	1.57	11.6	28	15	62	1.0	0.72	0.024	69	62	177	299

Treatment 2		\$C	\$B	\$W	\$M	FAT	RE	Marb	CW	DOC	Milk	HP	SC	YW	WW	BW	CED
	EPD	299	177	62	69	0.024	0.72	1.0	62	15	28	11.6	1.57	127	70	3.5	7
	%	10	10	35	35		25	15	20		35		15	20	25		

Treatment 3		\$C	\$B	\$W	\$M	FAT	RE	Marb	CW	DOC	Milk	HP	SC	YW	WW	BW	CED
	EPD	299	177	62	69	0.024	0.72	1.0	62	15	28	11.6	1.57	127	70	3.5	7

Figure 2. An Example of Different Treatment and Control Group Used in a Prediction Task

Finally, at the end of the experiment, participants were asked to complete a survey composed of herd composition, decision-making, and demographic characteristic questions related to their own cattle operations. (IRB approval: 21-368 EX 2108)

Econometric Analysis

We employed multiple probit regression models to estimate the likelihood of accurate price prediction under three definitions of accuracy: (1) within \$500 above or below the actual price, (2) within a $\pm 10\%$ deviation, and (3) within a $\pm 20\%$ deviation of the actual market price. These models were estimated both for the entire sample and for sub-samples stratified by state and breed to account for regional and breed-specific heterogeneity in price prediction behavior.

The probit model is appropriate when the dependent variable is binary, which in this study is, whether or not the participant's price prediction was “accurate” under a given accuracy

range. Probit models have been widely used in agricultural and behavioral economics to model binary outcomes related to producer decision-making (Adesina & Zinnah, 1993; Ingram et al., 2023; Lusk & Hudson, 2004). Moreover, the three definitions of accuracy were developed to reflect meaningful economic thresholds in real-world cattle marketing contexts. $\pm\$500$ threshold is commonly used in field experiments with producers to incentivize precision in judgment-based tasks (List, 2003). Participants have the incentive to be in this range in our study and is our baseline model. $\pm 10\%$ deviation reflects moderate forecast precision. A 10% price deviation could significantly affect a producer's cost structure, especially in high-value bulls, and is often used as a benchmark for acceptable predictive error in marketing and valuation research (Tonsor & Schroeder, 2006). Additionally, a $\pm 20\%$ deviation offers a broader margin for judgment and captures participants who had a general but not exact sense of the bull's value. It accounts for noise and individual valuation differences while still distinguishing between accurate and inaccurate predictions. The use of multiple definitions in our study also allows for robustness checks and captures the varying degrees of prediction accuracy under conditions that approximate realistic buyer expectations in cattle markets.

Equations 1 models the probability of accurate price prediction for the full sample under three definitions of accuracy: within $\pm\$500$, $\pm 10\%$, and $\pm 20\%$ of the actual market price. In addition, Equations 1 was replicated three times to analyze sub-samples defined by breed used in the study (Angus, Simmental, and Hereford), using the $\pm\$500$ threshold as the dependent variable. Likewise, Equation 2 models the probability of accurate price prediction for the sub-samples defined by states (Tennessee, Alabama, West Virginia, and Iowa) in our study, focusing exclusively on the $\pm\$500$ accuracy criterion. The equations are written as follows:

$$\Pr(Y = 1|X) = \Phi(\beta_0 + \beta_1 TRT + \beta_2 ST + \beta_3 A + \beta_4 S + \beta_5 H + \beta_6 E + \beta_7 ER + \beta_8 GE + \beta_9 P + \beta_{10} CO + \beta_{11} CF + \beta_{12} RP + \beta_{13} DG + \beta_{14} T + \beta_{15} AGE + \beta_{16} M + \beta_{17} F) \quad (1)$$

$$\Pr(Y = 1|X) = \Phi(\beta_0 + \beta_1 TRT + \beta_2 A + \beta_3 S + \beta_4 H + \beta_5 E + \beta_6 ER + \beta_7 GE + \beta_8 P + \beta_9 CO + \beta_{10} CF + \beta_{11} RP + \beta_{12} DG + \beta_{13} T + \beta_{14} AGE + \beta_{15} M + \beta_{16} F) \quad (2)$$

where Y is the probability of an accurate price prediction, with one being the case where the participant's price prediction was accurate or zero otherwise; Φ is the standard normal cumulative distribution function; TRT is a treatment variable for participants assigned to particular treatment group (control (base), treatment 1, treatment 2 and treatment 3); ST is a categorical variable for the state (Tennessee (base), Alabama, West Virginia and Iowa) where the experiment was conducted; A is a binary variable for participants with Angus cattle in their operation (1=yes; 0=no); S is a binary variable for participants with Simmental cattle in their operation (1=yes; 0=no); H is a binary variable for participants with Hereford cattle in their operation (1=yes; 0=no); E is a binary variable showing if participants utilize EPDs in their evaluation of cattle (1=yes; 0=no); GE is a binary variable showing if participants utilize GE-EPDs in their evaluation of cattle (1=yes; 0=no); ER is a binary variable showing if participants utilize EPD ranks in their evaluation of cattle (1=yes; 0=no); P is a binary variable showing if participants utilize physical characteristics in their evaluation of cattle (1=yes; 0=no); CO and CF is the indicated confidence level of participants when making ordinary life decisions and financial decisions respectively, on a scale of 0 to 100, where 0 means not confident at all and 100 means extremely confident; RP denotes the subject's risk tolerance nature measured with a slider scale of 0 to 10, where 0 means participants are "completely unwilling to take risks" and a 10 means they are "very willing to take risks", indicating the decision-maker's risk-tolerance

level (Falk et al., 2018); *DG* measures the delayed gratification level of participants, on a slider scale of 0 to 10, where 0 means participants are “completely unwilling to give up something today” and 10 means participants are “very willing to give up something today” in order to benefit from that in the future; *T* measures the trust of participants, measured on a slider scale of 0 to 10 where, 0 means low trust of participants on others and 10 means participants have high trust on others; *AGE* is a variable for participants’ age; *M* is a binary variable for male participants in the study (1= male, 0=female) and *F* is a binary variable denoting if farm employment is full time job of the participant (1=Yes, 0=No). **Table 1** provides more detailed definitions of dependent and independent variables examined.

We further employed probit model to examine factors influencing participants’ ability to successfully differentiate bulls based on quality, categorized as low, medium, and high, using price as a proxy for quality. To construct the dependent variable, we first averaged the sales prices of six bulls from each quality (average of six bulls sold for lowest price, average of six bulls sold for medium price and average of six bulls sold for highest price) used in the experiment. Next, we calculated the average predicted prices submitted by each participant for bulls within each quality category. Participants were then coded as “1” if their average predicted prices consistently distinguished between all three quality categories (i.e., correctly ordering low, medium, and high), and “0” otherwise. This binary outcome was then modeled using a probit regression framework, incorporating the same set of explanatory variables as used in the previous models.

Table 1. Definitions of Dependent and Independent Variables Examined

Variables	Definition
Accurate Price Prediction (Y)	=1 if the price prediction is accurate; otherwise, zero
Treatment (TRT)	=0 if participants were randomly assigned to control group (base), =1 if the participants were randomly assigned to treatment 1, =2 if participants were randomly assigned to treatment 2 and =3 if participants were randomly assigned to treatment 3.
Tennessee	=1 if participant is in the Tennessee sample; otherwise, zero
Alabama	=1 if participant is in the Alabama sample; otherwise, zero
West Virginia	=1 if participant is in the West Virginia sample; otherwise, zero
Iowa	=1 if participant is in the Iowa sample; otherwise, zero
Angus	=1 if the participant utilizes Angus cattle; otherwise, zero
Simmental	=1 if the participant utilizes Simmental cattle; otherwise, zero
Hereford	=1 if the participant utilizes Hereford cattle; otherwise, zero
EPD (E)	=1 if the participant utilizes EPDs for bull evaluation; otherwise, zero
GEEPD (GE)	=1 if the participant utilizes GE-EPDs for bull evaluation; otherwise, zero
EPD Rank (ER)	=1 if the participant utilizes EPD % ranks for evaluation; otherwise, zero
Phenotype (P)	=1 if the participant utilizes physical traits for evaluation; otherwise, zero
Confidence: Ordinary Life (CO)	stated confidence level of participants when making ordinary life decisions, on a scale of 0 to 100, where 0 means not confident at all and 100 means extremely confident
Confidence: Financial Decision (CF)	confidence level of participants when making financial decisions, on a scale of 0 to 100, where 0 means not confident at all and 100 means extremely confident
Risk Preference (RP)	indicates the participants risk-tolerance level measured in a scale of 0 to 10, where 0 means participants are “completely unwilling to take risks” and a 10 means they are “very willing to take risks”

Table 1 continued

Variables	Definition
Delayed Gratification (DG)	delayed gratification level of participants, on a scale of 0 to 10, where 0 means participants are “completely unwilling to give up something today” and 10 means participants are “very willing to give up something today” to benefit from that in the future
Trust (T)	trust of participants on others, measured on a scale of 0 to 10 where, 0 means low trust of participants on others and 10 means participants have high trust on others
Age (AGE)	age of individual participant in the study
Male (M)	=1 if the participant is Male; otherwise, zero
Full Time Job (F)	=1 if farm employment is full time job of the participant; otherwise, zero

Research Hypothesis

This study hypothesizes that the way EPD (Expected Progeny Difference) information is presented affects participants' ability to accurately predict bull prices. Participants assigned to Treatment 1, where only EPD values were shown without percentile ranks, are expected to have lower prediction accuracy than those in the control group (H1a). Removing percentile-rank columns deprives producers of the within breed context that helps them translate raw EPD numbers into a “better than / worse than average” judgment. In a recent field experiment with 164 cattle producers, Ingram et al. (2023) found that participants using EPD percentile rank measures have increased probability of an accurate seed stock price prediction, holding all else constant. Genetic extension bulletins likewise emphasize that “knowing breed averages and percentile ranks is critical to identifying sires that fit a breeding objective” (Spangler, 2019). In contrast, Treatments 2, which includes full information but with economic selection indices placed first, are hypothesized to increase prediction accuracy of participants (H1b). Economic

selection indices (e.g., \$B, \$W) collapse multiple EPDs into a single profit-oriented score and are explicitly promoted as decision simplification tools. Placing these indices in the left most columns exploit the primacy effect, i.e. the EPD traits seen first receives disproportionate attention and recall (Bialkova et al., 2014; Bundesen, 1990; Rayner, 1998), so producers should reach more accurate valuations of bulls. Moreover, treatment 3 combines the primacy benefit of economic selection indices with the contextual loss from dropping percentile ranks. Because the net effect is theoretically indeterminate, we treat the expected sign as unknown a priori (H1c) and test it empirically.

Furthermore, we anticipate that producers' price expectations and their ability to accurately predict cattle prices are influenced by individual characteristics. Extensive literature indicates that EPDs and physical traits are key factors influencing bull prices at auction (Boyer et al., 2019; Brimlow & Doyle, 2014; Jones et al., 2008; Kessler et al., 2017; McDonald et al., 2010; Tang et al., 2020; Vanek et al., 2008; Vestal et al., 2013). Furthermore, drawing from previous studies, the inclusion of GE-EPDs should enhance prediction accuracy due to their greater reliability and comprehensiveness in evaluating genetic merit (Rolf et al., 2014; Van Eenennaam & Drake, 2012). Based on these findings, we expect that participants who incorporate EPD, GE-EPD values, percentile ranks, and phenotype details into their decision-making will be more likely to make accurate price predictions compared to ones who do not use them (H2).

We also consider that a participant's confidence in their predictions may affect the accuracy of those predictions. Prior research suggests that individuals with higher levels of confidence may be more prone to bias, often leading to overestimations and, consequently, less

precise predictions (Ingram et al., 2023; Mayraz, 2011). We, thus hypothesize that participants with high stated confidence will have lower prediction accuracy (H3a). Similarly, we expect that individuals with higher risk tolerance may be less accurate in their predictions (H3b), as they could be more susceptible to misjudging market signals (Mayraz, 2011). Conversely, participants scoring high in delayed gratification are likely to perform better (H3c), as this trait is associated with patience and more thoughtful decision-making (Duckworth & Seligman, 2005; Reyna & Wilhelms, 2017). Additionally, higher generalized trust is expected to be positively associated with accuracy (H3d), as trusting individuals are more likely to rely on presented, objective information such as EPDs and breed averages, rather than subjective instincts (Ainsworth et al., 2014).

The influence of breed usage within an operation on prediction accuracy is less clear. While it is reasonable to expect that familiarity with specific breeds could improve both confidence and valuation accuracy, this may be counteracted by overconfidence. In fact, a recent study by Ingram et al. (2023) found that cattle producers who used the same breed in their operations as those featured in the experiment did not make more accurate price predictions than others. Therefore, this study aims to further investigate the relationship between breed familiarity and prediction accuracy (H4).

Finally, we explore regional differences in price prediction accuracy by comparing participants from Tennessee (baseline) with those from Alabama, West Virginia, and Iowa. Prior work by Ingram et al. (2023) showed that Alabama participants had higher accuracy in predicting bull prices than those from Tennessee, possibly due to different regional familiarity

with EPDs and market practices. For West Virginia and Iowa, directional expectations remain uncertain due to limited previous research (H5).

Results and Discussion

Summary Statistics

Table 2 provides the summary statistics of the independent variables used in the study across the pooled sample. About 80% of the sample has Angus cattle in their operation while only 27.98% of producers have Simmental cattle and 32.72% of producers have Hereford cattle in their operations. We asked respondents to report the source of information they usually use while evaluating cattle and found that majority of the producers utilize phenotypes of cattle (90.48%) as the major source of information for the evaluation of cattle followed by use of EPDs (80.36%), percentage rank of EPDs within breed (62.5%) and GE-EPDs (50%) respectively.

Moreover, we asked participants to indicate their decision-making behavior and general preferences in life. We found that the mean confidence level of participants on ordinary life decisions is 80.25 which is greater than the mean confidence level of participants on financial decisions (75.42). This highlights that the participants are less confident when it comes to financial decision making like buying a bull than a decision making in their day-to-day life. The mean risk preference score of participants was 6.46, indicating that participants were moderately likely to take risk while making a decision. Further, the average time preference score of 7.46 indicates that on average, the producers believe in delayed gratification and are willing to give up something today to get benefited in the future. We found the mean trust score to be 6.39, suggesting a moderate trust of participants on others.

Table 2. Summary Statistics of Independent Variables Used in the Study

Variable	N	Mean*
Tennessee	208	101 (48.56%)
Alabama	208	30 (14.42%)
West Virginia	208	37 (17.79%)
Iowa	208	40 (19.23%)
Has Angus in herd	208	169 (80.00%)
Has Simmental in herd	208	66 (27.98%)
Has Hereford in herd	208	62 (32.72%)
Uses EPD	208	173 (80.36%)
Uses GE-EPD	208	110 (50%)
Uses Phenotype	208	192 (90.48%)
Uses EPD Rank	208	137(62.5%)
General Confidence [0,100]	208	80.25 (17.12)
Financial Confidence [0,100]	208	75.42(19.58)
Risk Tolerance [0,10]	208	6.46 (2.14)
Delayed Gratification [0,10]	208	7.46 (1.85)
General trust of others [0,10]	208	6.39 (2.26)
Age	208	43.11 (15.77)
Male	208	159 (76.44%)
Cattle business is a full-time job	208	83 (39.90%)

*Values in parenthesis are either percent or standard deviation of the sample

Additionally, about 76.44% of the producers that took part in our study are male and is justified as the cattle business industry is mostly male dominated in U.S. The average age of producers that participated in our study is 43.11 years and about 39.90% of them reported cattle business to be their full-time job.

The mean price prediction accuracy across tasks and treatments is displayed in **Table 3**. The prediction was measured as an accurate prediction when it was within the range of \$500 above and below the actual price. Similarly, those who made prediction outside the bound of \$500 below and above the actual price were recorded as inaccurate prediction. The mean

prediction accuracy of producers randomly placed in treatment 2 (EPDs with percentile rank but flipped right to left) was found to be highest (25.99%) among the treatment groups followed by mean prediction accuracy of participants placed in treatment 1 (23.33%), treatment 3 (22.22%) and the control group (21.43%) respectively.

Table 3. Average Prediction Accuracy for Bull Prices across Tasks and Treatments

Task	Treatment 1 (N=42)	Treatment 2 (N=54)	Treatment 3 (N=59)	Treatment 4 (N=53)
1	0.00%	3.70%	8.47%	7.55%
2	14.29%	16.67%	22.03%	9.43%
3	14.29%	22.22%	20.34%	11.32%
4	21.43%	20.37%	30.51%	30.19%
5	9.52%	14.81%	22.03%	13.21%
6	28.57%	38.89%	30.51%	32.08%
7	21.43%	27.78%	22.03%	26.42%
8	38.10%	38.89%	42.37%	39.62%
9	35.71%	24.07%	38.98%	33.96%
10	9.52%	12.96%	18.64%	18.87%
11	26.19%	31.48%	38.98%	37.74%
12	42.86%	38.89%	54.24%	37.74%
13	14.29%	3.70%	5.08%	0.00%
14	26.19%	37.04%	33.90%	35.85%
15	47.62%	35.19%	30.51%	32.08%
16	0.00%	1.85%	8.47%	1.89%
17	9.52%	18.52%	11.86%	7.55%
18	26.19%	16.67%	28.81%	24.53%
Average	21.43%	23.63%	25.99%	22.22%

This suggests flipping the current industry standard arrangement of EPDs in a bull catalogue to place economic selection indexes, such as \$M (Maternal Weaned Calf Value), \$W (Weaned Calf Value), \$B (Beef Value), and \$C (Combined Value) first before other growth, carcass and management indexes will result in more accurate price prediction by producers.

Results from Probit Models

Table 4 presents the results from three probit models examining the likelihood of participants successfully predicting bull sale prices within three accuracy thresholds: $\pm\$500$, $\pm 10\%$, and $\pm 20\%$. Each model incorporates the treatments, states, breeds used in operation, valuation methods, confidence index, risk tolerance, and individual characteristics. Compared to participants in control group, participants in Treatment 2 were significantly more likely to predict bull sale prices accurately within $\pm\$500$ ($p < 0.1$). However, the effect was not statistically significant in the $\pm 10\%$ and the $\pm 20\%$ models. This might be because the participants had an incentive to be within the $\pm\$500$ range (the base model in our study) and not the other ranges which we included later in our analysis. This suggests that the arrangement or format of EPD profile in Treatment 2 might have helped participants improve price prediction accuracy, particularly when they had the incentive to do so. Likewise, Respondents from Iowa were consistently more likely to predict accurate prices across all thresholds compared to the participants from Tennessee, with strong statistical significance ($p < 0.01$ for $\pm\$500$ and $\pm 20\%$, $p < 0.05$ for $\pm 10\%$). This might be because of the regional differences in experience, education, or familiarity with cattle valuation practices across the states. Participants who had Simmental cattle in their operations had significantly better prediction accuracy within the $\pm 10\%$ model ($p < 0.05$), suggesting that breed-specific knowledge or preference might influence evaluation skill.

Table 4. Probit Results of Successful Prediction Probabilities for All Participants

Variable	+/- \$500 (1)	+/- 10% (2)	+/- 20% (3)
Treatment 1	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)
Treatment 2	0.04* (0.02)	0.03 (0.02)	0.04 (0.02)
Treatment 3	0.02 (0.02)	0.02 (0.02)	0.03 (0.02)
West Virginia	-0.01 (0.02)	-0.02 (0.02)	-0.01 (0.03)
Alabama	0.01 (0.02)	0.01 (0.02)	0.01 (0.02)
Iowa	0.06*** (0.02)	0.04** (0.02)	0.09*** (0.02)
Angus	-0.01 (0.02)	-0.02 (0.02)	-0.01 (0.02)
Simmental	0.02 (0.02)	0.03** (0.01)	0.01 (0.02)
Hereford	0.01 (0.02)	-0.01 (0.01)	0.01 (0.02)
EPDs	0.01 (0.03)	0.02 (0.02)	0.01 (0.03)
GE-EPDs	0.03* (0.02)	-0.01 (0.02)	0.03* (0.02)
Physical	0.05 (0.03)	0.01 (0.03)	0.02 (0.04)
Rank EPDs	0.04** (0.02)	0.05*** (0.02)	0.03 (0.02)
Confidence – Ordinary Decision	0.01 (0.0)	0.01 (0.0)	0.01 (0.00)
Confidence – Financial Decision	-0.01 (0.0)	-0.01 (0.0)	-0.01 (0.00)
Risk Preference	-0.01** (0.0)	-0.01* (0.0)	-0.01* (0.00)
Delayed Gratification	0.01* (0.0)	0.01 (0.0)	0.01 (0.00)
Trust	0.01* (0.0)	0.01 (0.0)	0.01* (0.00)
Male	0.02 (0.02)	0.01 (0.02)	0.01 (0.02)
Age	-0.01 (0.0)	-0.01 (0.0)	-0.01 (0.00)
Cattle business is full time job	0.01 (0.02)	-0.01 (0.02)	-0.01 (0.02)
Constant	1.3*** (0.2)	1.39*** (0.2)	-0.74*** (0.17)
N	3744	3744	3744
Log-Likelihood	-1990.32	-1760.8556	-2404.4522
Pseudo R-squared	0.018	0.017	0.012

Note: ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Additionally, participants who reported using ranked EPDs as a tool when buying bulls were significantly more likely to make accurate prediction both in the $\pm\$500$ and $\pm 10\%$ models ($p < 0.05$ and $p < 0.01$, respectively). The use of GE-EPDs also showed a significant positive effect in the $\pm\$500$ and $\pm 20\%$ models ($p < 0.1$), emphasizing the potential utility of genomic-enhanced decision-making tools. This result aligns with our hypothesis (H2) that participants who utilized more advanced selection tools were better able to make accurate valuations of the bulls in the experiment.

Participants who were more risk tolerant exhibited significantly lower prediction accuracy across all models ($p < 0.05$ or $p < 0.1$). This suggests that participants with a higher risk tolerance are more prone to optimism bias, leading them to overestimate bull prices that exceed the actual market value. This result is consistent with the study done by Ingram et al. (2023) where risk tolerance was inversely related with price accuracy. Similarly, higher delayed gratification and trust levels were associated with improved prediction accuracy in the $\pm\$500$ and $\pm 20\%$ models ($p < 0.1$), indicating that buyers who are more patient or exhibit greater levels of trust may make more thoughtful or informed decisions leading to increased accuracy consistent with previous studies from Duckworth & Seligman (2005), and Reyna & Wilhelms (2017). However, most demographic variables, including gender, age, and whether cattle production was the participant's full-time job, were not statistically significant.

Table 5 presents the marginal effects from the probit models estimating the probability of participants making accurate price predictions within $\pm\$500$ range, analyzed by state.

Participants in Tennessee who had Simmental bulls in their operation were 5 percent more likely to accurately predict bull values compared to those who did not ($p < 0.05$).

Table 5. Probit Results of Successful Prediction Probabilities across States (Accuracy: +/- \$500)

Variable	Tennessee	West Virginia	Alabama	Iowa
	(4)	(5)	(6)	(7)
Treatment 1	0.01 (0.03)	-0.02 (0.07)	-0.02 (0.06)	0.07 (0.07)
Treatment 2	0.04 (0.03)	-0.02 (0.07)	0.13 (0.09)	0.11 (0.07)
Treatment 3	0.01 (0.03)	-0.05 (0.10)	0.01 (0.06)	0.11 (0.08)
Angus	-0.02 (0.03)	-0.02 (0.07)	0.01 (0.08)	-0.10 (0.08)
Simmental	0.05**(0.02)	0.03 (0.06)	0.07 (0.07)	0.01 (0.04)
Hereford	-0.01 (0.02)	0.06 (0.06)	-0.01 (0.05)	-0.02 (0.06)
EPDs	0.04 (0.03)	-0.10 (0.14)	-0.45**(0.19)	0.09 (0.10)
GE-EPDs	-0.02 (0.02)	0.09 (0.07)	0.04 (0.06)	-0.05 (0.60)
Physical	0.12*** (0.03)	0.02 (0.10)	0.10 (0.11)	0.00 (0.00)
Rank EPDs	0.01 (0.02)	0.09 (0.06)	0.23*** (0.05)	0.07 (0.06)
Confidence – Ordinary Decision	0.01 (0.01)	-0.01 (0.01)	0.01 (0.01)	-0.01 (0.01)
Confidence – Financial Decision	-0.01**(0.01)	0.01 (0.01)	-0.01 (0.01)	0.01 (0.01)
Risk Preference	0.01 (0.01)	-0.01 (0.02)	-0.01 (0.01)	-0.02 (0.01)
Delayed Gratification	0.02**(0.01)	0.02 (0.01)	-0.01 (0.02)	0.01 (0.01)
Trust	0.01 (0.01)	-0.02*(0.01)	0.03*** (0.01)	-0.01 (0.01)
Male	0.02 (0.02)	-0.09 (0.10)	0.05 (0.04)	-0.07 (0.08)
Age	0.01 (0.01)	0.01 (0.01)	-0.01 (0.01)	0.01 (0.01)
Cattle business is full time job	0.02 (0.03)	0.17*** (0.06)	-0.08 (0.06)	0.04 (0.06)
Constant	-1.69*** (0.32)	-1.6 (0.99)	-1.7*** (0.6)	-0.33 (0.73)
N	1818	540	666	720
Log-Likelihood	-924.51	-247.79	-334.09	-433.50
Pseudo R-squared	0.019	0.069	0.084	0.016

Note: ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Additionally, participants from Tennessee, who utilize physical appearance of cattle while selecting bulls were positively and significantly associated with higher prediction accuracy (12% higher) than those who do not utilize the physical appearance of bull while making a bull selection decision. In Alabama, both the use of ranked EPDs and reliance on physical appearance were associated with significantly higher predictive accuracy. Interestingly, in West Virginia, participants who reported cattle as their full-time job were 17 percent more likely to predict prices successfully ($p < 0.01$). These findings suggest that the impact of cattle breed in operation, cognitive behavior, and use of different information for selection, on price prediction accuracy varies by state, likely due to differences in market conditions, producer experience, and familiarity with different selection tools.

Table 6 presents the probit regression results examining prediction accuracy, within each breed category; Angus, Simmental, and Hereford, used across 18 prediction tasks (6 per breed). For Angus bulls, Treatment 3 (i.e., economic selection indices placed first in EPD profile without percentile ranks) was positively and moderately associated with a higher probability of accurate price predictions, suggesting participants benefited from using EPD profile with economic selection index placed first before other indexes. Iowa producers also exhibited significantly greater prediction accuracy for Angus bulls, potentially reflecting regional familiarity or market experience with this breed. The utilization of GE-EPDs and ranked EPDs had significant positive effects on accuracy, indicating that producers utilizing these tools in their selection decision were better able to estimate Angus bull prices. Risk-tolerant individuals (higher risk preference) were less accurate, and males had a significantly higher probability of successful predictions relative to other genders. Age showed a small but statistically significant negative effect, implying

Table 6. Probit Results of Successful Prediction Probabilities across Breeds Used in Experiment

Variable	Angus (8)	Simmental (9)	Hereford (10)
Treatment 1	0.03 (0.03)	0.01 (0.04)	-0.04 (0.03)
Treatment 2	0.05 (0.03)	0.05 (0.04)	0.01 (0.04)
Treatment 3	0.07*(0.03)	0.02 (0.04)	-0.04 (0.04)
West Virginia	0.01 (0.04)	-0.02 (0.04)	-0.01 (0.04)
Alabama	0.03 (0.03)	-0.02 (0.04)	0.01 (0.03)
Iowa	0.08**(0.04)	0.03 (0.04)	0.07*(0.04)
Angus	-0.03 (0.03)	0.01 (0.04)	-0.01 (0.03)
Simmental	0.05** (0.03)	0.04 (0.03)	-0.02 (0.03)
Hereford	0.01 (0.03)	0.01 (0.03)	-0.01 (0.03)
EPDs	-0.01 (0.04)	0.04 (0.05)	0.01 (0.04)
GE-EPDs	0.05*(0.03)	-0.01 (0.03)	0.05*(0.03)
Physical	0.01 (0.05)	0.02 (0.06)	0.10**(0.04)
Rank EPDs	0.06**(0.03)	0.04 (0.03)	0.02 (0.03)
Confidence – Ordinary Decision	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Confidence – Financial Decision	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Risk Preference	-0.01**(0.01)	-0.01 (0.01)	-0.01 (0.01)
Delayed Gratification	0.01 (0.01)	0.01 (0.01)	0.01* (0.01)
Trust	0.01 (0.01)	-0.01 (0.01)	0.01 (0.01)
Male	0.08*** (0.03)	-0.04 (0.03)	0.03 (0.03)
Age	-0.01* (0.01)	0.01 (0.01)	-0.01 (0.01)
Cattle business is full time job	0.03 (0.03)	0.02 (0.04)	-0.03 (0.03)
Constant	-1.13*** (0.35)	-1.17*** (0.32)	-1.68*** (0.35)
N	1248	1248	1248
Log-Likelihood	-590.43	-739.75	-615.27
Pseudo R-squared	0.049	0.016	0.030

Note: ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

younger producers performed slightly better in accurately predicting bull prices than older participants.

The results were less pronounced in Simmental category. Most demographic and cognitive variables were not statistically significant, suggesting a more uniform prediction pattern across different producer types. For Hereford bulls, Iowa producers had a significantly higher probability of making accurate predictions ($p < 0.1$). Likewise, utilization of GE-EPDs and physical appearance by participants were positively associated with prediction accuracy. Delayed gratification also showed a weak positive influence, possibly indicating that producers with longer-term perspectives were better at accurate price prediction. Overall, these results show that accurate price prediction of seedstock bull does not solely depend on the tools or information producers are given, it also differs by breed.

Furthermore, **Table 7** presents the probit regression results examining the factors that influence participants' ability to accurately differentiate bulls based on quality, categorized as low, medium, and high, using price as a proxy for quality. Results of probit model showed that being from Iowa significantly increased the likelihood of accurately predicting quality differentiated bulls, suggesting that producers from Iowa may have greater familiarity or experience with quality-based price assessments. Similarly, results showed that participants utilizing GE-EPDs and Rank EPDs in their selection decision, were significantly more likely to differentiate bulls based on their quality. However, while treatments 2 and 3 had positive marginal effects, their impacts were not statistically significant.

In terms of individual cognitive traits, confidence in ordinary decisions was positively and significantly associated with prediction accuracy ($p < 0.05$), implying that self-assurance in

Table 7. Probit Results of Successful Prediction Probabilities of Quality Differentiated Bulls

Variable	dy/dx	standard error	p-value
Treatment 1	-0.009	0.089	0.917
Treatment 2	0.131	0.092	0.154
Treatment 3	0.138	0.094	0.140
West Virginia	0.117	0.105	0.265
Alabama	0.113	0.093	0.229
Iowa	0.238**	0.095	0.012
Angus	-0.044	0.089	0.617
Simmental	-0.006	0.068	0.935
Hereford	-0.053	0.069	0.438
EPDs	-0.116	0.109	0.290
GE-EPDs	0.174**	0.077	0.025
Physical	0.203	0.126	0.107
Rank EPDs	0.207**	0.083	0.012
Confidence – Ordinary Decision	0.007**	0.003	0.018
Confidence – Financial Decision	-0.003*	0.002	0.095
Risk Preference	-0.010	0.016	0.534
Delayed Gratification	0.013	0.018	0.460
Trust	-0.002	0.015	0.911
Male	0.022	0.081	0.790
Age	-0.001	0.002	0.726
Cattle business is full time job	-0.124	0.088	0.161
Constant	-2.566***	0.980	0.009
N		208	
Log-Likelihood		-111.33	
Pseudo R-squared		0.182	

Note: ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

everyday choices may translate into more confident and accurate judgments of quality differentiated bulls. Conversely, confidence in financial decisions had a negative effect ($p < 0.1$), which, while only marginally significant, could imply overconfidence causing participants to misjudge the quality of bulls.

Conclusion

This study explored how different EPD (Expected Progeny Difference) profile arrangements in bull sale catalogs influence seedstock producers' ability to accurately predict bull sale prices. Using a lab-in-the-field experimental design, we examined the cognitive and informational factors that affect accurate price prediction, as well as breed-specific and regional influences. Our results offer valuable insights into the decision-making patterns of seedstock producers and underscore the potential benefits of modifying EPD profile arrangement to enhance price prediction accuracy and thus accurate decision making.

Our analysis revealed that the arrangement of EPDs significantly influences price prediction accuracy. Specifically, producers in Treatment 2, who received a flipped layout with economic selection indexes (\$M, \$W, \$B, \$C) placed first, demonstrated the highest mean price prediction accuracy. This suggests that emphasizing economic selection indexes in catalogs can enhance producers' evaluation accuracy by helping them better connect genetic merit with economic value. This finding is crucial, especially in cattle industry where subtle differences in genetic traits can translate into significant financial implications.

The role of advanced selection tools emerged as a key determinant of predictive success. Producers who reported using Ranked EPDs and GE-EPDs consistently performed better in identifying accurate bull prices. These results suggest that familiarity with and reliance on more

sophisticated genetic tools can enhance a producer's ability to make informed price evaluations, providing empirical support for the growing emphasis on genomic-enhanced decision-making in cattle production.

Cognitive characteristics also played an important role. Participants with higher trust scores and greater willingness to delay gratification were more likely to predict bull prices accurately, indicating that patient and trusting individuals may approach decisions more thoughtfully. In contrast, those with higher risk tolerance consistently underperformed, supporting the hypothesis that risk-tolerant individuals may overestimate value due to optimism bias. Interestingly, while general confidence in ordinary decisions improved performance in differentiating bull quality, overconfidence in financial decisions appeared to have the opposite effect, possibly due to misjudgment of value signals.

Geographic differences also contributed significantly to prediction accuracy. Producers from Iowa consistently outperformed their counterparts from other states across all models and thresholds, which could reflect regional differences in market experience, access to educational resources, or operational scale. Additionally, state-level analyses showed that the impact of breed familiarity, use of physical appearance, and cognitive traits varied by location, emphasizing the importance of local context in decision-making behavior.

When examining prediction accuracy by breed category, Angus bulls demonstrated the clearest relationship between treatment and prediction success. Here, participants in Treatment 3, who viewed profiles with economic selection indexes placed first, showed improved accuracy, reinforcing the value of EPD profile restructuring. For Simmental and Hereford bulls, fewer

statistically significant differences were observed, suggesting that breed familiarity and perceived breed value may mediate the influence of EPD profile design.

Lastly, producers' ability to distinguish bulls by quality (proxy of price for which bull was sold)—low, medium, and high—using predicted prices further reinforced the importance of both informational tools and individual traits. Producers who utilized GE-EPDs and Ranked EPDs, and those from Iowa, were significantly better at correctly differentiating bulls by quality. This highlights the critical role of decision support tools in helping producers evaluate and compare genetically differentiated animals in a market setting.

Overall, this study provides evidence that altering the visual arrangement of EPD profiles, particularly prioritizing economic selection indexes, can lead to more accurate price predictions among producers. Furthermore, cognitive traits and familiarity with selection tools significantly influence decision-making effectiveness, suggesting that future educational efforts should not only promote the use of genomic tools but also help producers recognize how their cognitive biases may influence economic decisions.

These insights have important implications for bull catalog design, seedstock marketing strategies, and educational programs aimed at improving producer decision-making. Future research could expand on this work by testing similar interventions in real-world sales settings, incorporating a broader range of breeds and production systems, and exploring how digital tools or training programs could further enhance valuation accuracy.

While this study provides meaningful insights into producer decision-making and the influence of EPD profile design on price prediction accuracy, several limitations should be noted. The lab-in-the-field setting, though realistic, cannot fully replicate the financial stakes or

complexity of live bull auctions, which may limit the external validity of findings. Self-reported cognitive traits (e.g., confidence, trust, risk preference) may be influenced by bias, affecting measurement accuracy. The study focused on three common breeds—Angus, Simmental, and Hereford—limiting generalizability to operations using other breeds. Additionally, factors such as producers’ experience in beef cattle industry, and specific marketing channels used by producers were not included. These limitations suggest that while our findings are informative and statistically robust within the study context, caution should be taken when extending the conclusions to broader populations or different production systems. Future research can build on these limitations by conducting field trials in live sale settings, exploring more diverse cattle breeds, incorporating additional behavioral variables, and refining predictive thresholds based on producer-specific tolerance for valuation error.

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CHAPTER II

IN-STORE SHOPPING BEHAVIOR FOR VALUE-ADDED CHEESE

Abstract

The decline of small dairy farms in the United States has prompted producers to explore value-added strategies, such as farm-direct specialty cheese, to enhance profitability and capture a greater share of the consumer food dollar. This study investigates consumer preferences and in-store purchasing behavior for value-added cheese products using eye-tracking technology in a farm retail setting in East Tennessee. A total of 98 participants were randomly assigned to either a graphical or video informational treatment before shopping with eye-tracking glasses in the store, followed by a post-purchase survey. Descriptive analysis revealed that 64.7% of total expenditures were on cheese products, with type and price rated as the most influential purchase attributes. Ordinary Least Squares (OLS) regression indicated that purchase frequency, consumer satisfaction, and residential location significantly affected total spending, whereas treatment type and group shopping did not. Logistic regression results showed that holding and reading package information strongly increased the likelihood of purchasing cheese products ($p < 0.01$), while other intrinsic and extrinsic cues, including tasting, social interactions, and looking at the processing plant, were not significant predictors. Eye tracking video analysis revealed that 65.45% of participants followed an anticlockwise shopping path, with high shoppers concentrated on the cheese, tasting, and cashier areas. These findings provide actionable insights for small dairy farms to optimize store layout, product placement, and communication strategies to increase sales of value-added cheese products. The study contributes to the growing literature on consumer decision-making for farm-direct value-added dairy products and offers actionable strategies to enhance small farm profitability.

Introduction

Dairy industry in United States is experiencing a significant transformation, marked by a sharp decline in the number of small dairy farms. From 2007 to 2022, United States saw a decline of more than 50% in small dairy farms, largely driven by financial instability and the difficulty of competing with larger, more efficient operations (Jafri et al., 2024; McDonald et al., 2020). Moreover, rising costs for inputs like feed and fertilizer have made it difficult for smaller farms to remain profitable (Jones et al., 2022). In Tennessee, for example, the number of dairy farms has dropped from 2,400 in 1975 to fewer than 170 in 2022 (C. Zaring, 2022). This trend highlights the economic pressures faced by dairy operations with small-scale operations encountering additional struggles to compete relative to larger farms who benefit from economies of scale. For instance, between 2005 and 2018, farms with fewer than 200 cattle had negative net returns, while larger operations saw more consistent profits (USDA ERS, 2019). Similarly, in Tennessee, dairy farms have experienced a net loss on milk production, underlining the need for innovative solutions to enhance profitability (C. Zaring, 2022).

One promising strategy for small dairy farms is production of value-added products, which involves transforming raw commodities into higher value products like specialty cheese (Jafri et al., 2024). This approach can help farmers capture a larger share of the consumer dollar and diversify income streams, thus offering an opportunity to increase profitability (Cucagna & Goldsmith, 2018). In fact, since the farm share of the consumer food dollar—defined as the portion of each dollar spent by consumer on food that goes to farmers for raw agricultural commodities—has steadily declined over the past decades, many farmers and agribusinesses have sought alternative strategies to remain financially viable. In 2008, for example, farmers

received only 11.6 cents of every retail food dollar, with the remaining share going to processors, distributors, marketers, and retailers (Canning, 2011). This shrinking share underscores how little revenue farmers retain relative to downstream actors, especially in traditional commodity systems. As a response, more agribusiness firms and small producers are implementing downstream value-adding strategies—such as processing raw milk into cheese, branding, and/or selling directly to consumers—to capture a larger portion of the consumer dollar and stabilize income streams (Cucagna & Goldsmith, 2018; Kampen, 2011).

While there is existing research on consumer preferences for general dairy products, there is limited understanding of consumers purchasing behavior and preference for value-added products like specialty cheeses. Furthermore, use of eye-tracking technology in understanding consumer behavior specifically for dairy products in retail settings is limited. In this context, our study assesses consumers' preferences and shopping behavior for value-added local farm cheese products using eye-tracking technology in a retail setting.

This study was conducted at a dairy farm with an on-farm retail store in east Tennessee. Data was obtained from a total of 98 complete responses and was collected using eye tracking glasses and a survey instrument. The study was conducted in three stages: 1) participants were randomly assigned to one of the treatment groups (video or graphical treatment) 2) participants wore eye-tracking glasses while shopping in the store and made their purchases, and 3) participants completed a post-purchase survey addressing perceptions and demographic characteristics.

The broad objective of this research is to understand consumer preferences and buying behavior for value-added cheese products and assist local dairy producers in enhancing business

sustainability through value-added marketing insights. The specific objectives of this research are to evaluate the effect of different communication strategies (i.e., video vs. still graphic) on consumer preferences for cheese products and to identify key behavioral and socio-demographic factors influencing preferences for local farm-direct cheese products. Moreover, this study seeks to identify key intrinsic and extrinsic cues attached to the consumers' in-store shopping journey that influences purchasing decisions for cheese products. By uncovering consumer shopping behavior and preferences for value-added cheese products, this research provides valuable insights for small dairy farmers to develop effective marketing strategies and improve their competitiveness.

Literature Review

U.S. and Tennessee Dairy Industry

The U.S. dairy industry has undergone significant structural transformation over the past two decades, particularly among small- and medium-scale operations. Between 2007 and 2022, the number of small dairy farms in the United States declined by over 50%, driven by persistent financial instability, low farmgate prices, and limited ability to compete with larger-scale operations (Jafri et al., 2024). Similarly, the Southeastern U.S. experienced a decline in dairy farms, with a 7% reduction in licensed dairy farms between 2019 and 2020 (USDA NASS, 2021). In Tennessee alone, the decline in dairy farms is particularly stark, with fewer than 170 remaining in 2022 compared to 2,400 in 1975 (C. Zaring, 2022).

Larger dairy operations benefit from economies of scale, which reduce average production costs per unit. From 2005 to 2018, dairy farms with fewer than 200 cattle consistently experienced negative net returns, while those with 500 to 1,000 cattle generally achieved positive

returns. Farms with over 1,000 cattle saw positive net returns in 77% of those years (ERS, 2019). These economic pressures incentivize the consolidation of dairy farms into larger operations or their exit from the industry altogether (MacDonald et al., 2018). In Tennessee, the scenario is worse with dairy farms losing over \$4 more per 100 pounds of milk compared to the average U.S. dairy herd (C. Zaring, 2022). Rising costs for inputs like feed and fertilizer have made it difficult for smaller farms to remain profitable (Jones et al., 2022). In addition, off-farm costs, including marketing, processing, wholesaling, distribution, and retailing, account for over 60 cents of every dollar spent on milk (USDA NASS, 2024). The USDA's marketing bill analysis further highlights how increased marketing costs have reduced the farmer's share of the consumer dollar, defined as the portion of each dollar spent by consumer on food that goes to farmers for raw agricultural commodities (Canning, 2011). This decline in the farm share has been a key motivation for producers to pursue value-added strategies aimed at recapturing a larger portion of that consumer dollar through downstream activities like cheesemaking, branding, and direct-to-consumer sales (Cucagna & Goldsmith, 2018; Kampen, 2011).

Value Addition and Specialty Cheese

The value addition of products at the farm level plays a crucial role in enhancing the economic sustainability and competitiveness of agricultural enterprises. By transforming raw agricultural commodities into higher value products, farmers can capture a larger share of the consumer dollar and diversify their income stream (Jafri et al., 2024; Kampen, 2011). Value addition offers farmers the opportunity to increase profitability and stabilize their income in an increasingly competitive agricultural market. By creating differentiated agricultural products—featuring unique quality, origin, or ethical characteristics—producers can command premium

prices and better absorb cost pressures from commodity markets (Bittmann et al., 2020).

Consumers are increasingly drawn to products offering exceptional taste, local origin, health benefits, and sustainability credentials (Gracia et al., 2025). Through value addition, producers align their products with such evolving preferences by emphasizing traceability, ethical sourcing, and sustainability.

Specialty cheese production has emerged as a promising form of value addition, enabling dairy farms to diversify income and buffer against commodity price volatility. In Wisconsin—a national leader in specialty cheesemaking—small and mid-scale farms have used artisan and regionally branded cheeses to improve margins and cultivate consumer loyalty (CIAS, 2003; Dairy Foods, 2011). These findings align with national trends observed by Jafri et al. (2024), who document how specialty cheese production supports financial resilience among small U.S. dairies, especially those adopting farmstead or local marketing models. In Tennessee, a state that has witnessed a dramatic drop in dairy farms—from over 2,400 in the 1970s to fewer than 170 in 2022 (C. Zaring, 2022)—a small but growing number of farms have embraced specialty cheese as a means of survival. Moss (2012) conducted a feasibility study evaluating the potential for on-farm processing and marketing among Tennessee dairy farms, concluding that value-added dairy enterprises, including cheese and yogurt production, are viable pathways to improving farm profitability, especially when targeted toward urban and specialty markets in cities such as Knoxville, Nashville, and Memphis. In fact, a recent study by Zaring et al. (2024) further underscores the expansion of value-added dairy enterprises in Tennessee. Their findings indicate that many farms either currently engage in or are planning on farm processing of products such as aged cheese, creamline milk, and ice cream. The study highlights how producers are

increasingly adopting vertical integration to enhance margins, extend product shelf-life, and build brand identity.

Product Attribute and Consumer Preference

Consumer preferences for farm value-added products are shaped by various product attributes, such as quality, origin, packaging, health benefits and so on, that interact in complex decision-making processes. Price continues to be a dominant influence, with consumers often associating higher price tags with superior quality and premium inputs (Zeithaml, 1988). At the same time, demand for locally sourced and regionally branded foods is increasing, as consumers perceive such products to be more authentic, fresher, and supportive of their local economy (Enthoven & Van Den Broeck, 2021; Hinrichs, 2016). Flavor, meanwhile, remains a fundamental driver of satisfaction and repeat purchase, with diversity in taste profiles enhancing consumer engagement and perceived product value (Enthoven & Van Den Broeck, 2021).

Consumer behavior toward value-added dairy products—such as cheese, yogurt, and butter—is of no difference and is shaped by multiple product attributes including price, origin, quality, packaging, sustainability, authenticity and so on. For instance, a study by Wang et al. (2015) asked consumers to state their willingness to pay for six different cheese attributes—local, artisan, organic, farmstead, renewable energy production, and price—and found that quality-seeking cluster of consumers were significantly influenced by all attributes presented and were willing to pay 15-25% more for these attributes, while price sensitive group was influenced by local attribute and price. This result underscores that while price is critical, combined attribute cues, especially local, farmstead and artisan branding, significantly elevate perceived value for specialty cheese products. A study by Gedikoglu & Parcell (2014) surveyed Midwestern

consumers, revealing that 25% of consumers preferred handmade cheese and 10% preferred farmstead origin, while 53% were willing to pay about 20% more for domestic artisan cheese over commercial processed cheese types. This research highlights the premium consumers place on artisanal and farmstead cheese origin and perceived quality cues in dairy.

Communication Strategy

In recent years, producers have increasingly adopted both video- and text-based communication strategies to engage consumers and promote value-added agricultural products. While direct comparative studies on the impact of video versus text communication in the agricultural sector remain limited, broader research indicates that video-based strategies, especially those featuring product usage or storytelling, can significantly enhance purchase intentions. For example, Cheng et al. (2022) conducted experimental studies showing “usage videos”—demonstrating product in context—yield significantly higher purchase intention than simple appearance videos. Similarly, Hu et al. (2025) found that high-definition, emotionally engaging videos improved trust and behavioral intent through both central (rational) and peripheral (emotional) routes. Videos promoting agritourism (analogous to farm-based products) enhanced visitor intention via immersive storytelling and cognitive clarity (Hu et al., 2025). Meng et al. (2024) reported that short-form video ads embodying trustworthiness, expertise, and attractiveness positively affected consumer purchase behavior. Qu et al. (2017) conducted an experimental investigation into the effects of short online videos on U.S. consumer attitudes toward locally produced food products. Their study revealed that even a 30-second video depicting product quality and community benefits significantly improved consumer attitudes

compared to no video exposure. This demonstrates that video-based messaging effectively enhances consumer perception and engagement with farm-derived value-added offerings.

Meanwhile, text-based communication strategies, including detailed product descriptions, ingredient narratives, and origin labels, facilitate deeper cognitive engagement. These textual formats support central-route processing—critical for consumers seeking transparency, certification integrity, or detailed product knowledge (Petty & Cacioppo, 2012; Russo et al., 2021). Graphic or text-based contents, while less emotionally engaging, provides depth through clarity and perceived informational value; however, studies show that video content still produces stronger purchase intentions compared to written or graphic content, mediated by perceived value and reduced psychological distance (Qin et al., 2024). While text and images support detailed attribute comprehension—effective for consumers processing via central persuasive routes—they often lack the emotional and immersive impact of video formats.

Together, evidence underscores that strategic use of video content, particularly short, informative, and emotionally resonant formats, can significantly enhance consumer trust and purchase intention, while textual and graphic media serve complementary roles in providing transparency and product detail critical for informed choice.

Eye-tracking and In-store Search Behavior

Visual attention is the gateway to information processing in consumer choices; products must be noticed before they can influence decision-making. Without visual attention, consumers cannot perceive or evaluate product cues effectively (Plassmann et al., 2015). Eye-tracking technology (ETT) offers a way to measure visual attention through key metrics such as fixations (moments when the eye remains stationary, allowing cognitive processing) and saccades (rapid

movements between fixations during which no visual information is absorbed due to vision suppression. Vision suppression refers to the brief inability to perceive visual input during saccades, meaning no information is taken in during those moments (Vu et al., 2016). Detailed imagery and attribute understanding thus occur during fixations. These metrics help researchers quantify how consumers interact with online and retail environments, and product displays.

Vu et al., (2016) demonstrated how design features of food images influence both gazing behavior and decision time, highlighting that longer fixations enhance information processing and contribute to more considered decisions. Similarly, Monteiro et al. (2020) found that attention to wine labels, measured via fixation duration, was a significant predictor of purchase intention. This effect was amplified when bottles displayed awards or were intended for social consumption environments.

In a dairy-specific eye-tracking study, Riswanto et al. (2025) found that consumers spent significantly more time fixating on packages with clean, simple designs and prominently placed information. Additionally, emotionally appealing visuals and trust cues, such as sustainability or certification labels, enhanced purchase intention. The study also confirmed that fixation count and duration are predictive of product choice. Moreover, a comprehensive meta-analysis by Li et al. (2024) reviewed eye-tracking studies in online shopping and found a consistent relationship between visual attention, particularly fixation duration, and purchase intention. Products that were fixated on longer were significantly more likely to be purchased. Additionally, price tags, discount labels, and central screen placement were key factors influencing gaze behavior. The authors also noted a bias toward centrally located content, reinforcing the importance of layout design. Though focused on digital environments, these findings highlight how attention-based

cues guide consumer evaluations, which can inform both online and offline merchandising strategies.

Additional evidence from in-store contexts supports the predictive value of visual attention. In an eye-tracking experiment on garden plants, Behe et al. (2015) found that high-involvement consumers demonstrated longer fixation durations and greater focus on product-specific information, such as branding and benefits. These consumers engaged in more deliberate evaluation, suggesting that value-added claims (e.g., “farm-direct,” “organic”) may be especially persuasive for this segment. Conversely, low-involvement shoppers displayed less attention to detailed information but were still influenced by product elements that received higher visual attention. Overall, the study underscores that visual attention mediates the relationship between involvement and choice, reaffirming its importance in shaping purchase behavior.

Additionally, in a controlled supermarket shelf study, Gidlöf et al. (2017) further validated that visual attention is a robust predictor of consumer choice. Products that received longer and more frequent fixations were more likely to be selected. Although initial attention was often guided by pre-existing preferences, the final decision was shaped by the intensity and pattern of gaze behavior. Shelf design factors, such as central positioning and visual contrast, strongly influenced where consumers looked, reinforcing the role of layout in guiding purchasing behavior. These findings support the principle that “looking is buying,” and visual attention plays both reflective and mediating roles in the consumer choice process.

Visual attention plays a critical role in consumer product choice within physical retail settings. A study by Chen et al. (2021) found that shoppers navigating grocery store aisles exhibit a lateral bias, tending to focus more on items positioned on their right-hand side.

Additionally, contrary to the traditional assumption that eye-level placement draws the most attention, the study revealed that consumers are more likely to fixate on items positioned approximately 14.7 inches below eye level, closer to chest height. This suggests that optimal product placement may occur lower on shelves than previously assumed.

To examine how consumers distribute their visual attention across product displays, (Bogomolova et al., 2020) conducted an eye-tracking investigation on unit price label formats in grocery retail. They utilized heat maps, visual overlays indicating fixation density with varying colors, to identify which label designs attracted the most attention. The study found that labels formatted with larger fonts, strategic positioning, and color contrast significantly attracted visual fixations, and that products with high-attention price labels were more likely to be purchased. These findings emphasize the importance of clear, well-designed informational cues in driving consumer engagement and preference.

In another study, Huddleston et al. (2023) explored visual and behavioral cues influencing consumer decisions in retail greenhouse settings. They found that intrinsic product interaction, such as looking at or physically touching a plant, was the most common and influential behavior affecting purchase decisions. While external cues such as interactions with employees (34%) and mobile phone use (19.4%) were also present, direct engagement with the product itself played a more significant role in shaping customer behavior. This finding reinforces the idea that tactile and visual engagement can be more influential than third-party information during the decision-making process.

Eye-tracking thus offers an objective lens into the dynamics of consumer behavior, providing valuable insights into where, when, and how consumers allocate attention—and how

that attention translates into actual decisions. Despite the growing body of literature, very few studies have applied eye-tracking in farm-direct retail environments, which often present unique situational contexts, such as visible production facilities, agritourism elements, and direct farmer-consumer interactions. These contexts may distinctly shape visual attention and, consequently, consumer behavior.

Materials and Methods

Study Procedure

For our study, data was collected at a dairy farm with an on-farm retail store in east Tennessee on May 04, 2024, and September 07, 2024. The study was an interception study, meaning potential participants were recruited on-site and were shoppers at that store. Prior to the study, recruitment materials (promotions, advertisements) were distributed by the retailer to their mailing list and on their social media sites. A total of 98 participants were recruited for the experiment with each participant receiving a \$20 incentive after signing the consent form and prior to participating in the study. All the participants were at least 18 years of age. Before admitting participants to the experiment, they read and signed the consent form which informed them about the nature of the study, time commitment, associated risks and monetary incentives. Participants were made aware that they could leave the experiment at any time. The study was conducted in three stages. In the first stage, participants were randomly assigned to a treatment (graphic or video; discussed shortly). In the second stage, participants walked into the store wearing eye tracking glasses and made their purchasing decisions. In the last stage, upon completion of stage two (i.e., they had completed their purchase or left the retail store),

participants completed a post-purchase survey. All study procedures and protocols were approved by the University of Tennessee's Institutional Review Board (24-08051-XM). ETTs were used to collect data during the first and second stages of the experiment. In stage one, tables were located outside of the store with two desktop computers (31-inch OLED monitors, 1920 x 1080 resolution) equipped with eye-tracking cameras. iMotions software in conjunction with Smart Eye Aurora stationary cameras (120 Hz) were used to collect visual attention metrics in stage one. Participants were randomly assigned to one of the desktop computers. Each desktop computer displayed a different treatment. The first treatment was a graphics treatment while the second treatment was a video. The graphics treatment was an image (portrait) with pictures of feeding cattle, cattle being milked, and trays with white cheese. These pictures were on the left of the graphic while text information was on the right. The images and text were taken from the video treatment. The dairy farm operation (milking) information provided through both the graphics and video treatments were identical, meaning people received comparable information just in a different format. There was no predetermined time limit on how long the participants could view the graphic treatment. Conversely, the video treatment was 1:48 minutes long and included a female subject. The subject delivers a well-structured treatment script. For the video script and the visual treatment (**Figure 5**), please refer to the appendix.

The experiment started with calibrating the eye-tracking cameras to the participants where they fixate on a focal point that moves around the screen. The stationary eye-tracking cameras use a 9-point calibration system followed by a secondary 4-point system meaning the focal point stops at 9 locations, followed by 4 different locations. This results in increased accuracy given that the camera is calibrated to each individual's eyes. Next, respondent's eye

movements were recorded as they read (graphic) or watched (video) the information treatment. After viewing the treatment, participants were fitted with eye-tracking glasses (Smart Eye Pupil; 60 Hz) to capture their visual attention in the retail store while shopping. They were not given a time limit for shopping. The shopping portion was considered complete when they purchased their items or exited the shop. In stage three, participants completed a survey which included questions related to participant purchasing behavior, familiarity with the farm, level of satisfaction, personal preferences, and demographics. Receipts were collected from participants to record their purchases made during the experiment.

Data

The receipts collected from participants were entered manually in Microsoft Excel. The total amount they spent on the store and the amount they spent on each cheese and non-cheese products were recorded along with the quantity of each product they bought. The participants who were randomly assigned to video treatment (n=45, 45.92%) were coded 1 and those assigned to graphical treatment (n=53, 54.08%) were coded 2. Participants were also distinguished based on whether they were shopping alone (coded “0”) or in group i.e. with family, friends and children (coded “1”).

The participant’s videos recorded inside the store were uploaded to the pupil cloud, an eye-tracking visualization platform by Pupils Labs. Researchers then viewed the videos, coded the shopper’s start and end time of shopping and recorded the total time of the shopping trip. More specifically, we recorded the total time of the shopping trip from the shopper’s first fixation inside the shop to the time they pushed the door handle to exit the store and return to the study desk area. We viewed videos and recorded significant times of interest (TOIs) for each

participant in accordance with the study done by Huddleston et al. (2023), with few modifications to suit our study. The TOIs included six extrinsic cue actions (1) use of a cell phone, (2) interaction with other shoppers, (3) fixation on other customer, (4) interaction with store employees, (5) read or viewed wall poster, (6) looked at cheese processing plant (cheese processing plants could be seen through a transparent glass window from inside the store) and two intrinsic cue actions (1) tasted sample of cheese and (2) held and read the package information. All the cue actions for each participant were recorded as binary variable (=1 if they attended the cue action, otherwise zero). Participants were recorded to have attended the cue action if they had at least three fixations on the cue. We also recorded whether the participant bought any cheese products or not and coded it as a binary variable (=1 if they bought any cheese product, otherwise zero). Of 98 participants, video data from 43 were incomplete or poorly tracked or missing and was omitted for subsequent analyses.

The participant's video was further viewed and analyzed to find the path followed by each participant inside the store. Major areas inside the store were identified as four products shelves, ice-cream parlor, bread table, cheese trough, cheese tasting area, meat and drink cooler, gifts shelf, baskets area and the cashier area. Each participant's path was coded in the order they visited the areas identified above (=1 to the area visited first, =2 to the area visited second and so on with a maximum of 12 to area visited last). We also looked at movement of participants across the cheese trough and differentiated them as single pass (those who pass one time through the cheese trough), more than one pass, and back forth (participants who were constantly moving back and forth from cheese trough to other areas). All these movements were coded as binary variable (=1 if they show a particular movement, zero otherwise).

The survey used in the study was administered in-person via Qualtrics. Participants were asked about their knowledge on farm direct products using a seven point Likert scale, purchase frequency for farm direct dairy products, monthly dairy expenses, where do they generally buy their dairy products from, familiarity with the store, travel distance to the store, their online purchasing habit and socio-demographics that included their gender, education, ethnicity, household size and income. Moreover, we asked participants to rank different attributes based on their relative importance while buying cheese products on a scale of 1-7, where 1 represented that the attribute is most important and 7 represented that the attribute is least important to them. Additionally, we asked participants to state their level of satisfaction with the purchase they made in the store, using a 5-point Likert scale. We also asked participants to consider the products they picked out to purchase in the store and to indicate the likelihood of repurchasing and recommending those products to others on a scale of 0 to 100, where 0 meant definitely not repurchasing or recommending the products and 100 meant that they have already repurchased/recommended the products and will continue to do so in future. The results survey variables can be found in result and discussion section of this paper.

Econometric Analysis

To investigate the determinants of participants' total spending in the store, we employed an Ordinary Least Squares (OLS) regression model with a log-linear transformation of the dependent variable. The dependent variable, denoted as T_i , represents the actual dollar amount spent by each participant, which we obtained directly from their receipts, and which ranged from \$0 to \$108.26. Because the spending data was right-skewed, consistent with consumer expenditure studies (Deaton & Muellbauer, 1980), we applied a natural logarithmic

transformation to the spending variable to better satisfy the normality and homoscedasticity assumptions of OLS.

To address the issue of zero spending values in our dataset, since the natural logarithm of zero is undefined, we applied a log-linear transformation by adding one to each observed spending value prior to taking the logarithm. Specifically, we used the transformation $\log(\text{total spending} + 1)$ to retain all observations in the analysis, including those with zero spending. This approach is commonly employed in empirical research to manage zero values in log-linear models without losing data (Manning & Mullahy, 2001). By doing so, we preserve the full sample and mitigate bias that could arise from excluding zero-spending participants. This addition was recognized and adjusted later when interpreting the results. We modeled T as a function of independent variables (i.e., treatment, shopping in group, demographic characteristics, shopping behaviors, purchase satisfaction, and purchase history). The econometric model can be written as:

$$T_i = \beta_0 + \beta_1 \text{Treatment} + \beta_2 \text{Group Shoppers} + \beta_3 \text{Purchase Frequency} + \beta_4 \text{Monthly Dairy Expense} + \beta_5 \text{Farm Visits} + \beta_6 \text{Purchase Satisfaction} + \beta_7 \text{Residential Area} + \beta_8 \text{Female} + \beta_9 \text{Household Size} + \text{error term}$$

where the treatment variable indicates whether a participant received the graphical treatment in the eye-tracking experiment, with the control (video treatment) group as the reference. Group shoppers capture whether the participant shopped with others, compared to solo shoppers.

Purchase frequency categorizes how often dairy product is purchased, with "never purchased" as the base category. Monthly dairy expense includes different spending brackets, referenced against those spending \$0.01-\$20 per month. Farm visits reflect the number of prior visits to the farm, with those who never visited serving as the baseline. Purchase satisfaction is a binary

indicator of whether the participant was extremely satisfied, compared to the moderately satisfied level. Residential area includes small town, suburbs, and urban areas, with rural area as the reference. Gender is represented by a female dummy variable, where males form the reference group. Finally, household size represents the total number of adults plus children present in the household.

We then examined how visual attention (eye-tracking data) and product-related cues influence consumers' likelihood of purchasing specialty cheese in the farm retail store using a logit model. Logistic (and probit) regression models are widely used in consumer choice research because they are designed for binary outcomes, such as whether a product is purchased or not, and allow estimation of the probability of purchase as a function of visual attention, intrinsic/extrinsic product cues, and experimental treatments (Behe et al., 2015; Chen et al., 2021; Gidlöf et al., 2017; Huddleston et al., 2023). Logistic regression is appropriate in this context because the dependent variable is binary, representing whether a participant purchased at least one cheese product ($Y = 1$) or did not purchase ($Y = 0$) during their shopping trip. The independent variables included treatment exposure, intrinsic cues ((1) tasted sample of cheese and (2) held and read the package information), extrinsic cues ((1) use of a cell phone, (2) interaction with other shoppers, (3) fixation on other customer, (4) interaction with store employees, (5) read or viewed wall poster, (6) looked at cheese processing plant), and shopping group composition. The model used to estimate the probability of a cheese purchase is specified as:

$$\Pr(Y = 1|X) = \beta_0 + \beta_1 \textit{Treatment} + \beta_2 \textit{Intrinsic Cues} + \beta_3 \textit{Extrinsic Cues} + \beta_4 \textit{Group Shoppers} \\ + \textit{error term}$$

where P_i represents probability of a shopper purchasing a cheese product. The treatment variable indicates whether a participant received the graphical treatment in the eye-tracking experiment, with the control (video treatment) group as the reference. Group shoppers capture whether the participant shopped with others, compared to solo shoppers. Intrinsic cues capture whether the participant attended the intrinsic cue explained above or not (reference group). Likewise, extrinsic cues capture whether the participant attended the specific extrinsic cues mentioned above or not (reference group). This model allows us to quantify how marketing treatments, visual attention to intrinsic and extrinsic product cues, and shopping in group context collectively influence the likelihood of purchasing specialty cheese.

Results and Discussion

Summary Statistics

Table 8 provides the summary statistics on average spendings across treatment groups and cheese and non-cheese products. The average amount spent by an individual in the store was \$21.49, with a minimum of \$0 and maximum of \$108.26. Participants in the graphic treatment spent \$21.81 on average, while those in the video treatment spent \$21.17. Likewise, participants who were in a group (with family, friends and children) spent \$26.17 on average, while those who shopped alone spent \$20.58. A Welch's test showed that the difference in spending between the two-treatment group was not statistically significant. About 54.32% of the participants reported that they were revisiting the store (i.e., had visited the store in the past). Those individuals who were repeat visitors may have heightened familiarity with the store, which might have overshadowed the treatment effect on participants' total expenditure due to having established product preferences.

Table 8. Average Amount Spent on Cheese and Non-Cheese Products by Treatment

Product Purchased	Video Treatment (N=45)	Graphical Treatment (N=53)	Total
Cheese Products (1)	12.57 (12.91)	15.02 (17.60)	13.80 (15.70)
10 oz. cheese block	5.75 (6.32)	8.38 (9.15)	7.07 (8.10)
7 oz. cheese block	2.04 (4.03)	1.21 (2.71)	1.63 (3.35)
Cheese bag	4.27 (8.93)	3.15 (9.97)	3.71 (9.50)
Cheese straw	0.52 (1.41)	0.24 (1.30)	0.38 (1.35)
Vols cheese	0.0 (0.00)	2.04 (10.45)	1.02 (7.88)
Non-cheese Products (2)	8.60 (7.94)	6.79 (11.72)	7.70 (10.23)
Total expenditure (1+2)	21.17 (14.85)	21.81 (19.99)	21.49 (17.84)

Note: A Welch's test was conducted for mean comparison across treatments. Values on parenthesis are standard deviation.

Regarding the products purchased, 64.7% of the total expenditures were on cheese products (including 10-ounce cheese, 7-ounce cheese, cheese bags, cheese straw and vols cheese) with 35.3% of the total expenditures being on non-cheese items (e.g., bread, curd, jam, jelly, bacon, salami, hoff sauce, sausage etc.). In monetary value, participants spent on average \$13.80 on cheese products while only \$7.70 on non-cheese products. On breaking it down further, while participants in the video treatment spent more on non-cheese products (\$8.60 vs. \$6.79) and less on cheese products (\$12.57 vs. \$15.02) than those in the graphic treatment, neither difference was statistically significant.

Out of the total amount spent on cheese products in the store, 50.65% was spent on 10-ounce cheese blocks, 11.30% was spent on 7-ounce cheese blocks, 27.56% was spent on cheese bags, 2.51% was spent on cheese straw and the remaining 7.98% was spent on Vols cheese (a specialty item co-branded with the University of Tennessee power-T). The three cheese items (10-ounce cheese, 7-ounce cheese and cheese bags) account for 89.51% of the total amount spent by participants.

Regarding relative importance, participants ranked cheese “type” (e.g., cheddar) to be the most important attribute when making a purchase decision with an average weighted ranking score of 1.47 (**Table 9**) followed by the other attributes like price (2.82), color (4.00), age (4.06), connection to farm (4.16), information on farm (5.33) and information on cheese making (6.17). Among the various attributes evaluated, only the perceived importance of color differed significantly across treatment groups ($p = 0.04$). Participants in the video group rated color to be less important (average weighted ranking = 4.38) than those in the graphic group (average weighted ranking = 3.70). No other attribute ratings (e.g., price, type, age, farm connection, farm info, or cheese making) differed significantly across groups. These results demonstrate that participants place more importance on internal product attributes than those that are external from product itself, like the products connection to a farm, information on farm and the cheese making process.

Table 10 presents the key socio-economic and demographic attributes of the respondents in our sample, alongside corresponding national-level statistics for comparison. The socio-demographic profile of the study participants reveals a predominantly female (59.78%) and

Table 9. Average Ranking of Attributes of Cheese by Participants (1-Very Important to 7-Least Important)

Attribute	Average Weighted Ranking	Overall Rank
Price	2.82	2
Age	4.06	4
Type	1.47	1
Color	4.00	3
Connection with farm	4.16	5
Information on farm	5.33	6
Cheese making process	6.17	7

Table 10. Participants Demographics and Socioeconomic Characteristic

Respondents Characteristics	Average (Standard deviation)	National Average
<i>Gender (n=92)</i>		
Male	37 (40.22%)	49.5%
Female	55 (59.78%)	50.5%
<i>Highest level of education (n=94)</i>		
College degree	67 (71.28%)	36.2%
<i>Ethnicity (n=93)</i>		
White	85 (91.40%)	57.1%
Hispanic	5 (5.38%)	19.4%
Black	0.00%	11.8%
Other race/ethnicity	3 (3.22%)	10.7%
Household size (n=94)	2.82 (1.41)	2.49
Household with children	32 (31.98%)	28.8%
<i>Household income (n=92)</i>		
Below \$50,000	21 (22.83%)	32.3%
Between \$50,000 - \$ 100,000	26 (28.26%)	28.8%
Between \$100,000- \$ 150,000	23 (25.00%)	17.4%
Above \$150,000	22 (23.91%)	21.5%

Source: National averages are from the U.S. Census Bureau, 2023 American Community Survey 1-Year Estimates (Tables DP05, S1501, S1101, and S1901).

highly educated (71.28% with a college degree) sample. Compared to national averages, the sample was less ethnically diverse, with 91.40% identifying as White. Participants also reported slightly larger household sizes (average = 2.82) and higher income levels, with nearly half earning above \$100,000 annually. These characteristics suggest that the study captured a more affluent and educated consumer segment.

In addition to collecting socioeconomic data, we also gathered information on participants' dairy shopping habits, including their familiarity with farm-direct products, purchase frequency, spending levels, satisfaction, and likelihood of repurchase, as summarized in **Table 11.**

Table 11. Participant's Shopping Behavior Collected via Survey

Survey Variables	Average
<i>Knowledge of farm-direct dairy product (n=93)</i>	
Very unknowledgeable	7.53%
Somewhat unknowledgeable	18.28%
Slightly unknowledgeable	10.75%
Neutral	9.68%
Slightly knowledgeable	21.51%
Somewhat knowledgeable	24.73%
Very knowledgeable	7.53%
<i>Purchase frequency of farm direct dairy product (n=94)</i>	
Never	31.91%
Once a month	37.23%
2-3 times per month	20.21%
Weekly	10.64%
<i>Monthly Dairy Spending (n=93)</i>	
\$0.01-\$20	12.90%
\$21-\$40	24.73%
\$41-\$60	38.71%
\$61-80	10.75%
\$81-\$100	6.45%
Above \$100	6.45%
<i>Familiarity with the store (n=93)</i>	62.37%
<i>Visit to the farm in past year (n=81)</i>	
This is my first visit	45.68%
1-3 visits	32.10%
4-6 visits	6.17%
7-9 visits	2.47%
10-12 visits	4.94%
13+ visits	8.64%
<i>Level of satisfaction with your purchase today (n=94)</i>	
Somewhat satisfied	10.64%
Extremely satisfied	89.36%
<i>Likelihood of repurchasing and recommending</i>	
Likelihood of repurchasing items you purchased today (n=94)	86.17 (23.60)
Likelihood of recommending items you purchased to others (n=92)	91.19 (17.46)
(On a scale of 0-100; where 0=not repurchasing/ recommending and 100= already repurchased/ recommended and will continue)	

Table 11 continued

Survey Variables	Average
<i>Perception of quality of the product you bought today (n=94)</i>	
Good quality	3.19%
Very good quality	24.47%
Excellent quality	72.34%
<i>Purchase value-added dairy products online (n=94)</i>	
Yes	4.26%
No	65.96%
No, but I will potentially in the future	29.79%
<i>Likelihood to repurchase the product bought today online (n=94)</i>	
Very unlikely	20.21%
Somewhat unlikely	7.45%
Neither likely nor unlikely	10.64%
Somewhat likely	39.36%
Very likely	22.34%
<i>Residential Area (n=94)</i>	
Rural	32.98%
Small town	24.47%
Suburban	32.98%
Urban	9.57%

Participants showed varying levels of familiarity and engagement with farm-direct dairy products. While only 7.53% considered themselves very knowledgeable, over 53% reported being slightly to somewhat knowledgeable. Despite this, 31.91% had never purchased farm-direct dairy products, with most purchases occurring once a month (37.23%). Most respondents spent between \$21 and \$60 per month on a dairy, and over 60% were already familiar with the store.

Nearly half (45.68%) were first-time farm visitors, while others had visited multiple times over the past year. Consumer satisfaction was notably high, with 89.36% extremely satisfied, and purchase intent was strong; respondents rated their likelihood to repurchase at 86.17 (SD = 23.60) and recommend products at 91.19 (SD = 17.46) on a 0–100 scale. Product

quality was rated as excellent by 72.34% of participants. While only 4.26% currently purchase value-added dairy products online, 29.79% expressed intent to buy it online in future. Regarding online repurchase behavior, 61.7% indicated being somewhat to very likely. Participants predominantly lived in rural (32.98%) or suburban (32.98%) areas, followed by small towns and urban areas. These findings suggest that while farm-direct dairy purchasing remains relatively limited in frequency and online adoption, there is strong consumer satisfaction, high perceived product quality, and substantial intent to repurchase, indicating a promising opportunity for expanding farm-direct and online value-added dairy markets, particularly among informed and engaged consumers in non-urban areas.

Factors Affecting Total Amount Spent

The results of the OLS regression show that the treatment and shopping in a group vs. alone did not significantly impact participants' total spending in the store (Table 12). Notably, participants who reported buying farm-direct dairy products once a month spent approximately 175.4% more compared to those who reported never bought farm-direct dairy product ($p < 0.01$; **Table 12**). However, participants who reported purchasing farm-direct dairy products 2–3 times per month or weekly did not exhibit significantly different total expenditures compared to those who reported never purchasing such products. This might be because monthly buyers may be stockpiling dairy products for the whole month, therefore they would have increased spending on dairy products at each purchase.

Table 12. OLS Results for Factors Affecting Total Amount Spent

Variable	Coefficient	Standard Error	p-value
Graphical Treatment	-0.246	0.251	0.332
Shoppers in group	0.353	0.341	0.306
Purchase once a month	1.013***	0.345	0.005
Purchase 2/3 times a month	0.275	0.350	0.436
Purchase weekly	0.619	0.449	0.174
Monthly Dairy Expense (\$21-\$40)	0.036	0.423	0.932
Monthly Dairy Expense (\$41-\$60)	0.505	0.471	0.289
Monthly Dairy Expense (\$61-\$80)	0.400	0.561	0.479
Monthly Dairy Expense (\$81-\$100)	-1.743**	0.657	0.011
Monthly Dairy Expense (\$100+)	0.615	0.748	0.415
Visited Farm 1-3 Times in Past	0.452	0.311	0.153
Visited Farm 4-6 Times in Past	0.005	0.575	0.992
Visited Farm 7-9 Times in Past	1.319	0.942	0.168
Visited Farm 10-12 Times in Past	0.313	0.636	0.624
Visited Farm 13+ Times in Past	0.296	0.536	0.584
Extremely Satisfied with Purchase	0.762*	0.412	0.07
From Small Town	1.016***	0.361	0.007
From Sub-urban	0.693**	0.294	0.023
From Urban Area	0.886*	0.480	0.071
Female	0.223	0.303	0.465
Household Size	0.013	0.018	0.49
Constant	1.996**	0.849	0.023
N		98	

Note: ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

In the regression model, the reference category for monthly dairy expense is the lowest expenditure group (\$0.01–\$20), and the remaining categories represent increasing intervals of \$20. Interestingly, among these, only the \$81–\$100 expenditure category is statistically significant ($p < 0.05$), suggesting that respondents in this group spent significantly less (82.6%)

in total compared to those in the lowest expenditure group. However, the other adjacent categories, both lower and higher values, were not statistically significant.

Participants who were extremely satisfied with their purchase spent 114.2 % significantly ($p < 0.1$) more than the ones who reported to be somewhat satisfied with their purchase.

Likewise, participants' residential location was significantly associated with their total spending. Compared to those living in rural areas (the reference group), participants from small towns spent approximately 176.2 % more on average ($p < 0.01$). Similarly, participants from suburban areas spent about 100% more ($p < 0.05$), while those from urban areas spent approximately 142.5% more, which was marginally significant ($p < 0.1$).

Moreover, first time visitors versus those who visited the retailer multiple times in the past had no significant differences in their spending. Result showed female participants spent approximately 25% more than male participants, though this difference was not statistically significant ($p = 0.465$). Similarly, household size had no significant impact on total spending.

Shopping Behavior

Video analysis of in-store shopping behavior revealed that 65.45% of participants followed an anticlockwise path, entering the store and moving to the right-hand side first. These findings align with Chen et al. (2021), who observed that shoppers tend to allocate greater visual attention to products on the right side of aisles, assuming product displays are equivalent on both sides. Although the density of products varied in this study, this result could have important implications on shelf and product placement to facilitate customer movement through the store.

On average, participants spent 445.31 seconds (~7.4 minutes) in the store with individuals shopping in groups spending more time (438.57 seconds) than the ones shopping

alone (291.03 seconds). Tasting the cheese sample (56.36%) and holding the cheese product to read the label (63.64%) were the most frequently employed intrinsic cues (**Figure 3**), supporting participants self-reported weighted average ranking of type and price to be the most important attributes participants value. Similarly, 67% of participants looked at the wall poster which provided price information and the availability of different types of cheese suggesting more evidence for how important these attributes are for shoppers. Additionally, video analysis results showed that very few participants (27.27 %) looked at the processing plant which was designed and placed at the current location to derive more consumer attention towards it. However, it is important to note that the plants were not operating when we carried out our study. This suggests that the farm outlet can redesign this space for more engagement and attention, and in return maximize profit. These results together suggest that graphical cues may influence visual

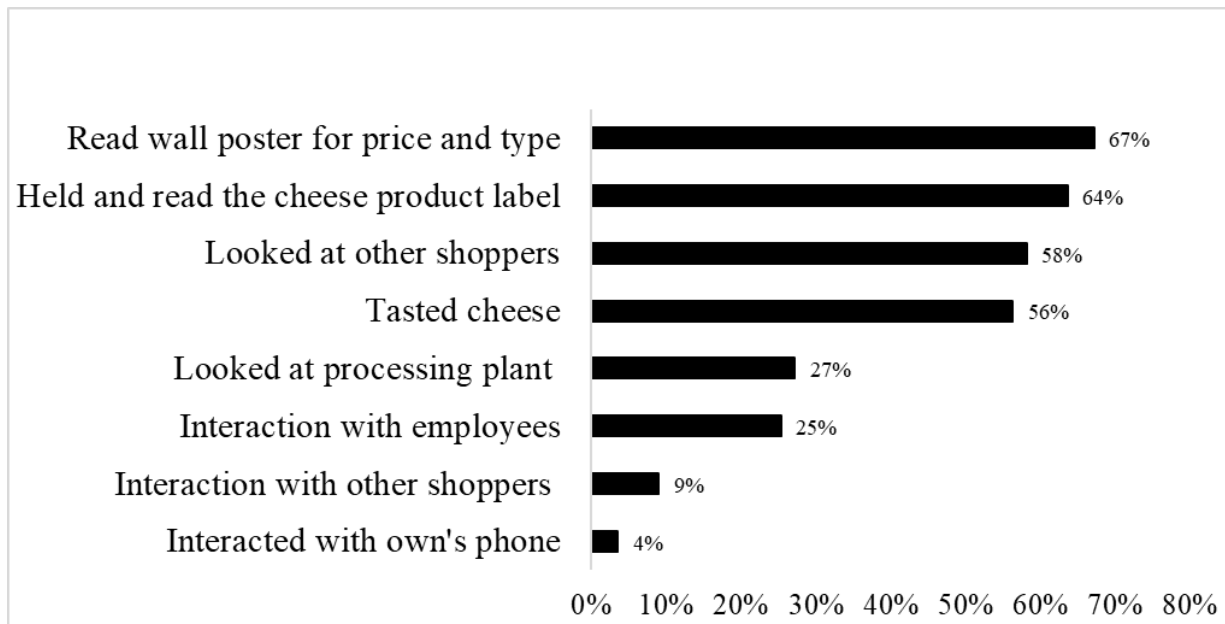


Figure 3. Shoppers Engagement with Intrinsic and Extrinsic Cues Inside the Store (N=55)

attention behaviors, especially toward social and product-related cues, even if overall shopping time and other interactions did not differ significantly.

Table 13 further summarizes differences in in-store shopping behaviors between the video and graphical treatment groups. Participants in the video treatment spent slightly more time in the store (400.62 vs. 379.57 seconds) and were more likely to move to the right side first (75% vs. 56%). They also engaged more with intrinsic cues, such as reading package information (75% vs. 52%, $p = 0.077$) and extrinsic cue, such as looking at other shoppers (71% vs. 44%, $p = 0.043$). Other behaviors, including tasting cheese, reading wall information, and interacting with employees or phones, showed no statistically significant differences between treatments.

Table 13. Comparison of Shopper's Attention for Cues across Treatments

Variables	Video Treatment Mean (SD)	Graphical Treatment Mean (SD)	p-values
Total time spent in store (sec)	400.62 (142.34)	379.57 (157.64)	0.605
Right hand side movement	75%	56%	0.134
Read package info*	75%	52%	0.077
Tasted cheese	64%	48%	0.235
Interacted with phone	4%	4%	0.980
Interacted with other shoppers	11%	7%	0.677
Looked at other shoppers**	71%	44%	0.043
Interacted with employee	32%	19%	0.288
Read wall info	68%	67%	0.927
Looked at processing plant	32%	22%	0.418
N	28	27	0.605

Note: A Welch's test was conducted for mean comparison across treatments. Values on parenthesis are standard deviation. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Table 14 presents the result of a logit model estimating the influence of the cues and experiential factors on participants' likelihood of purchasing cheese products. Results showed that the participants who held the cheese and read the package information were significantly more likely to buy cheese products than the ones who didn't hold and read the package label ($p < 0.01$). This finding underscores the importance of detailed product labeling in influencing consumer purchasing behavior.

Other experiential cues such as tasting the cheese, interacting with employees or other shoppers, or observing the processing plant did not show statistically significant associations with the likelihood of purchasing cheese product. Additionally, the variables for treatment group, group participation, and total time spent within the shopping environment were also not statistically significant.

Table 14. Logit Model Estimates for Cues Influencing the Likelihood of Buying Cheese Products

Variable	Coefficient	standard error	p-value
Treatment	0.688	1.232	0.577
Participants In Group	0.024	1.299	0.985
Total Time	0.002	0.005	0.637
Read Package Info	3.902***	1.332	0.003
Tasted Cheese	0.237	1.214	0.846
Interacted With Phone	0.000	0.000	-
Interacted With Other Shoppers	0.630	3.131	0.841
Looked At Other Shoppers	-1.584	1.106	0.152
Interacted With Employee	-1.312	1.499	0.381
Read Wall Info	-1.156	1.155	0.317
Looked At Processing Plant	-0.070	1.236	0.955
Constant	-0.471	3.015	0.876
N		55	

Note: ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Interestingly, looking at other shoppers showed a negative association, though not statistically significant ($p = 0.152$), possibly indicating that social observation may deter purchase in certain settings. Although the results were not significant, the presence of other shoppers has been shown to impact purchasing behavior (Huddleston et al., 2023) and future studies employing larger sample sizes in different retail settings could illuminate how social components influence purchasing behavior and shopping paths.

Moreover, through video analysis we tracked shoppers' initial orientation (< 1 minute) to different areas of the store (**Figure 4**) and the areas of high and low visits. We found 29.09% of the participants entered and visited shelf 1 first, followed by 25.25% proceeding directly to the tasting area, 18.18% to the cheese section, and 27.27% to other areas. A majority (61.82%) followed a right-to-left (counterclockwise) route, consistent with retail design logic that capitalizes on shoppers' tendency to turn right and circumnavigate the store (Chen et al., 2021). We further tracked each participant's visit to the areas (figure 4) inside the store and differentiated areas of high and low visits. The mapped areas of high visits were the cashier area (89.22%), cheese section (81.33%), and tasting zone (76.19%), shelf 1 (48.65%), shelf 3 (47.29%), and the meat & drink cooler (41.74%). In contrast, very low visits were observed at the baskets area (7.28%), ice cream (17.99%), shelf 4 (25.29%), shelf 2 (29.25%), and bread displays (34.06%). These patterns align with empirical mobility analysis in supermarkets, which shows that shoppers concentrate in perimeter zones and avoid congested interior spaces, optimizing flow and visibility (Gul et al., 2023). Understanding the shopping path and area of high (low) visits provides actionable insights into the farm's retail operations.

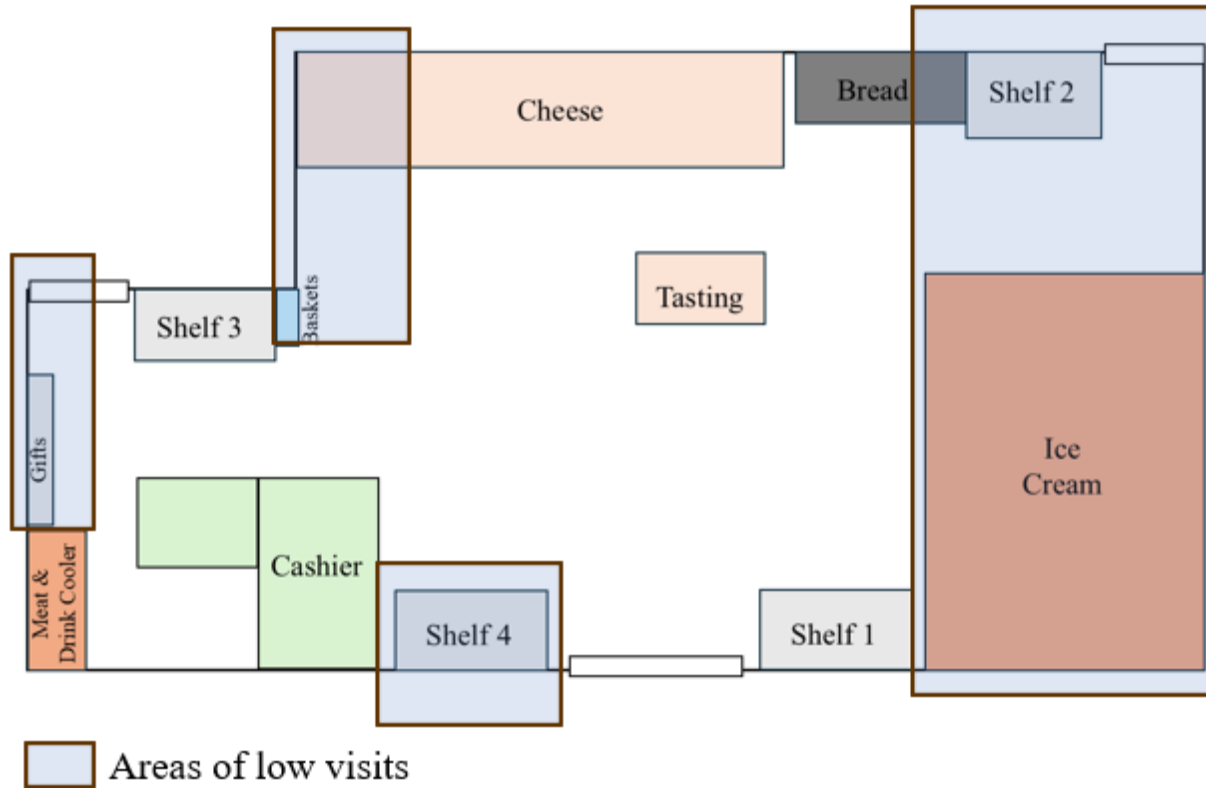


Figure 4. Layout of the Farm's Retail Store with Areas of Low (High) Visits (N=55)

By identifying high-traffic zones such as the cashier, cheese section, and tasting area, the store can strategically position high-margin or promotional products to maximize visibility and encourage impulse purchases. Conversely, low-traffic zones like the baskets area, shelf 4, and the ice cream section indicate opportunities for layout adjustments, improved signage, or promotional cues to redirect shopper flow. This approach aligns with evidence that strategic product placement and visual merchandising in high-visibility areas can significantly increase purchase likelihood (Chandon et al., 2009).

Conclusion

This study explored consumers shopping behaviors for value-added cheese products using a combination of experimental economics, eye-tracking technology, and post-purchase survey at a retail dairy farm store in Tennessee. The findings of this study offer valuable insights into consumers' shopping behavior which can help Tennessee's dairy industry in developing targeted marketing strategies to enhance profitability and long-term sustainability of their businesses.

Our results reveal that while treatment (video vs. graphic) and shopping in groups did not significantly influence total in-store spending, nuanced patterns in consumer behavior were evident. Most participants were repeat visitors, which may have reduced the observable impact of experimental treatments due to established familiarity and prior purchasing habits (e.g., knowing the store layout, having favorite products). These participants probably came up with a plan on how much to spend or what to buy from the store, causing the treatment they were randomly placed in or their group or individual visit to store to do nothing with the amount they spend in store.

Cheese products accounted for nearly two-thirds of all spending, underscoring the central role of cheese in driving revenue at the farm outlet. The 10-ounce cheese, 7-ounce cheese, and cheese bags comprised nearly 90% of total cheese product purchases. This indicates clear consumer preferences; however, it should be noted that the retailer was a value-added dairy operation where visitors likely anticipate cheese being the primary product sold. As such, the heightened spending on cheese and cheese-centric focus by customers aligns with anticipated and actual product availability. Future research could delve into this relationship by assessing

customers use of similar point-of-sale cues and purchasing behavior with similar products at different outlets at agritourism and mainstream retailers. In turn, targeted product development and inventory management could be assessed based on the different retail channels employed.

Sociodemographic characteristics and shopping behaviors provided further insights. Participants from small towns, suburban areas, and urban areas spent significantly more than their rural counterparts, suggesting that the population density where the customer lives is a strong predictor of purchasing behavior. These findings suggest that individuals residing in more urbanized environments tend to have higher spending levels, potentially due to increased purchasing opportunities, higher disposable income, or differing consumer behaviors compared to rural residents (Lacko et al., 2020). Gender and household size did not significantly impact spending. Interestingly, participants who reported buying farm-direct dairy products once a month spent significantly more, on average, when compared to participants who reported never buying farm-direct dairy products, which may reflect a stocking-up behavior not observed among more frequent buyers.

Eye-tracking and video analysis complemented these findings by analyzing the influence of in-store intrinsic and extrinsic cues. The direction of store navigation, primarily counterclockwise, suggests that product placement strategies should prioritize the right-hand side of the store to maximize consumer attention. Additionally, the most interacted with cues were intrinsic attributes such as cheese tasting and label reading, confirming participants self-reported weighted average ranking of product type and price as the most valued attributes. Likewise, over two-thirds of participants viewed wall posters displaying price and cheese types, further confirming participants ranking of these attributes. In contrast, only a small percentage of

participants engaged with the cheese processing plant, suggesting better utilization of the space for maximum returns.

Logit model estimates showed a strong, statistically significant effect of reading package information on the likelihood of purchasing cheese products. This highlights the importance of informative, engaging product labels in influencing consumer decision-making at the point of purchase. In contrast, interactive and observational experiences, such as employee interaction or observing other shoppers, did not significantly impact purchasing outcomes. These results suggest that small dairy farms can enhance consumer engagement and sales performance by emphasizing clear, appealing product labels and strategically focusing on product development and marketing of both high and low in demand cheese products.

While our study gives meaningful insights into consumers' shopping behavior for value-added cheese products in a retail setting, there are limitations of this research that must be acknowledged. First, the sample size of this study (N=98) was small, which limited the analytical scope of this research. However, many eye-tracking studies in consumer behavior use relatively modest participant counts (e.g. 30–40) yet still achieve high reliability through large numbers of fixation observations (120 Hz for the stationary cameras; 60 Hz for the glasses) and controlled experimental designs, such as studies on price attention in retail clothing (N =31) (Menon et al., 2016) or multimodal consumer choice prediction with eye tracking (N = 42) (Usman et al., 2025). Another limitation of this research is with the generalizability of the findings to broader consumer populations or to other farm retail outlets. Local context, consumer demographics, and cultural preferences may have influenced results and might not reflect broader market behavior across the U.S. Moreover, our study relied partially on self-reported data from post-shopping

surveys, which are subject to social desirability bias (Fisher & Katz, 2000). Participants may have over or under reported the importance of certain product attributes or their satisfaction levels, which could influence interpretation of the results.

Despite these limitations, our study offers valuable insights into consumer spending behavior, influence of communication strategies in consumers spending, the cues shoppers interact with while shopping, and how these factors influence buying behavior in an on-farm retail setting. Our study also contributes to the growing body of literature on consumer behavior in value-added agriculture.

Future studies with larger sample sizes, multiple treatment groups and more diverse samples from different regions and at different on-farm retail settings could be carried out based on this research to understand consumer shopping behavior more comprehensively. Additionally, use of automated software for video analysis in future might help in analyzing consumers shopping trips inside the store more precisely.

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Appendix

Video Treatment Transcription

“Hey y’all, I’m so excited to get to talk to you guys today and show you a little more about our operation. My name is Mary Lyndal, and this is my family’s farm. We are milking about 1,500 cows each day and also producing lots of delicious cheese. Cows that are well fed are happy cows, and happy cows produce us the best quality milk. We have a double-12 milking parlor. Cows will come in from the back and 12 will line up on each side, with a total of 24 cows being milked at a time. This usually only takes about 10-12 minutes. Did you know that cows actually like to be milked? How come you might ask, because it relieves all of that weight they’ve been carrying around! Although we are milking with some robots now, we still have automatic milking parlors at three of our other milking locations. This process is very simple, we start by cleaning off the teats, and then the milker is placed on each of the four teats on the udder. This milk is then used to make some of our favorite dairy treats like cheese.”

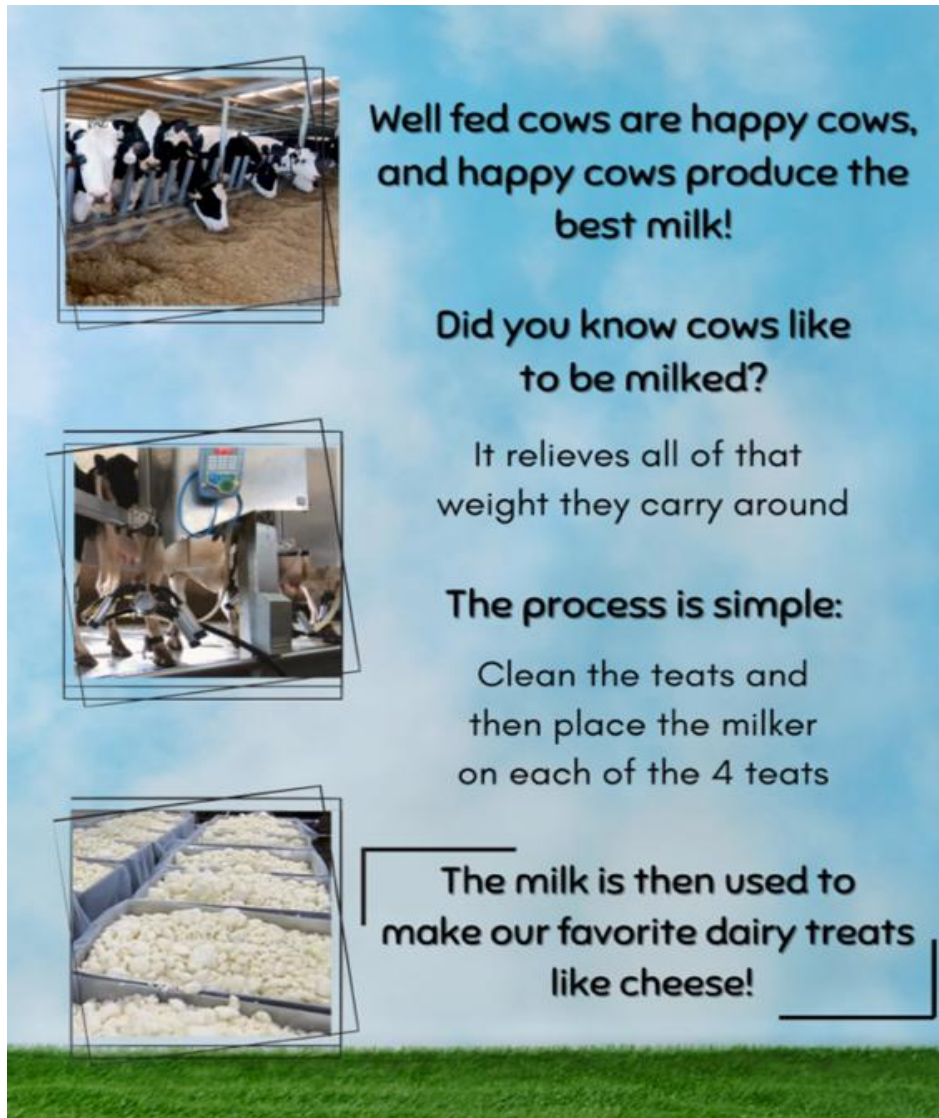


Figure 5. Graphical Treatment Used in the Study

VITA

Awasar Ghimire was born and raised in Nepal. He completed his Bachelor of Science in Agriculture from Tribhuvan University, Nepal, where he developed a strong interest in Agricultural Economics. Motivated to expand his academic and research capabilities, he joined the University of Tennessee, Knoxville, where he pursued a Master of Science degree in Agricultural and Resource Economics. His research interests include crop and livestock production economics, dairy economics, behavioral and experimental economics, and applied econometrics. After graduation, Awasar will be joining Department of Agricultural and Applied economics at Virginia Tech to pursue a Ph.D. program in Economics (Agriculture).