Recognizing Non-Pecuniary Labor Benefits in Technology Adoption: Evidence from Automatic Milking Systems in U.S. Dairy Farming

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Abstract

This study examines pecuniary (e.g., labor cost savings) and non-pecuniary (e.g., improved flexibility) labor benefits in technology adoption through a discrete choice experiment involving 212 dairy farmers in the U.S. Midwest focusing on automatic milking systems. Results reveal that farmers value flexible time 2.17 times more than hired labor savings, suggesting practitioners differentiate non-pecuniary benefit from pecuniary ones and utilize multiple methods to assess preference heterogeneity for robustness: we consistently found that farmers experienced labor difficulties favor hired labor savings, whereas those with secondary income value both benefits less. For other characteristics (e.g., herd size), preference heterogeneity is ambiguous.

Keywords: farmers preferences, willingness to pay, farm automation, milking systems

JEL codes: D22, Q12, Q16

Introduction

Labor-saving technologies are fundamental in advancing efficiency in agriculture (Edan, Han & Kondo, 2009; Gallardo & Sauer, 2018). These technologies reduce labor inputs, improve management practices and well-being (Staccioli & Virgillito, 2020). The literature emphasizes the adoption of technologies must be economically viable (Sunding & Zilberman, 2001) and the primary motivation for adoption is often the promise of labor benefits —typically referring to labor input savings and improved labor efficiency (Gallardo and Sauer 2018).

Studies on labor-saving technologies generally fall into two categories: cost-benefit analyses to inform potential adopters' decisions, and economic studies that analyze adoption behavior, industrial impact, and policy design (Dedrick, Gurbaxani & Kraemer, 2003; Salfer et al., 2017; Lowenberg-DeBoer et al., 2020). These studies have traditionally estimated the total value of labor benefits by measuring the difference in total labor input hours before and after adoption—often termed "labor savings"—without distinguishing the source or nature of the change, and then multiplying the difference by the market wage rate.

However, discussions in the literature (Edan, Han, and Kondo 2009; Gallardo and Sauer 2018) have observed that potential adopters often value not only the commonly recognized pecuniary benefit of hired labor savings, but also non-pecuniary benefits, such as the improved flexibility, lifestyle, and overall well-being. These findings challenge the traditional approach: when non-pecuniary labor benefits are overlooked or when analyses rely solely on labor input differences and market wage rate, the total value of labor benefits may be misrepresented, leading potential adopters to make decisions based on incomplete information.

In this study, we investigate non-pecuniary benefits in the technology adoption decision-making process, focusing on the Automatic Milking System (AMS) in U.S. Midwest dairy farming. The U.S. Midwest is the leading region for milk production, contributing 24.16% of the nation's supply (USDA, 2024). Similar to other agricultural sectors, dairy farmers represent one of the most burdened workforces, averaging over 60 hours of on-farm work per week (USDA, 2018). The industry depends on a consistent farm labor supply but currently faces severe labor shortages (Hertz & Zahniser, 2013; Zahniser, 2018).

AMS offers a potential solution to the labor challenges in dairy farming by automating the milking process using robotic arms and sensors, allowing cows to walk in and be without human intervention (Cogato et al., 2021). The primary motivations for AMS adoption are reduced labor inputs and improved flexibility by freeing farmers from rigid milking schedules, while the main barrier is substantial investment (Latvala & Pyykkonen, 2005; Svennersten-Sjaunja & Pettersson, 2008; Cogato et al., 2021). The economic returns of AMS remain inconclusive. Prior cost-benefit analyses have emphasized the pecuniary benefits of hired labor savings, estimating the economic value of AMS adoption based on market wage rates (Latvala & Pyykkonen, 2005; Bijl et al., 2007; Salfer et al., 2017; Hansen et al., 2019; Gargiulo et al., 2020).

A handful of qualitative survey studies have noted that non-pecuniary benefits play an important role in AMS adoption. For instance, Schewe & Stuart (2015) found that lifestyle benefits, particularly increased family time and recreation, are among the most important factors in AMS adoption. Peña-Lévano, Burney & Beaudry (2023) reported that improved flexibility is perceived positively by farmers and encourage adoption. However, quantitative evidence regarding the value potential adopters place on these non-pecuniary benefits remains scarce.

Despite mixed findings on economic returns, over 6,000 dairy farms worldwide had adopted AMS by 2018, and adoption continues to grow globally (Mathijs, 2004; Gallardo & Sauer, 2018). In the U.S., AMS adoption remains limited as of 2024, which may be due to the previously sufficient supply of immigrant and migrant labor (Becerra 2020; Gutiérrez-Li et al. 2025), lack of information about AMS benefits, and the perceived hassle of reconstruction and adaptation (Mathijs 2004; Svennersten-Sjaunja and Pettersson 2008; Hansen, Herje & Höva 2019). However, with changes to immigration administration anticipated in 2025, the labor structure and conditions may shift.

To the best of our knowledge, this is the first study to differentiate and quantify potential adopters' valuation of the non-pecuniary labor benefits of AMS adoption. This study contributes to two strands of literature. First, it advances the cost-benefit analysis of AMS by offering a more complete view of benefits to inform stakeholders. We elicit potential adopters' willingness to pay (WTP) for two quantitatively comparable benefits, hired labor savings (pecuniary) and increased owner flexible time (non-pecuniary), under scenarios involving trade-offs. Our findings underscore the importance of differentiating and incorporating non-pecuniary labor benefits both qualitatively and quantitatively in future analyses to better inform adoption decisions.

Second, by evaluating non-pecuniary labor benefits, which have often been omitted or subsumed under pecuniary benefits in prior research, our study contributes to the broader literature on the economics of technology adoption and provides insights into adoption behavior. Furthermore, since preferences and valuations of non-pecuniary attributes often vary among potential adopters (Farzin, 2009; Ortiz & Sarrias, 2022), we evaluate preference heterogeneity based on farmer characteristics though multiple methods for robustness, including farm size, income source, confidence in future profitability, experience with labor difficulties, risk aversion, and time discounting preferences.

Experimental Design

The currently low adoption rate of AMS in the U.S. limits available farm-level data. Moreover, without placing potential adopters in decision-making contexts involving trade-offs and controlling for variation in AMS models, farm structures, and production types—as done in a DCE—it is challenging to elicit farmers' valuations of pecuniary and non-pecuniary labor benefits. To address these limitations, we employed a stated preference approach using a DCE implemented through mailed surveys, which are effective for reaching farmers (Pennings, 2002).

DCE has been widely applied to study technology adoption (Ortiz, Avila-Santamaría & Martinez-Cruz, 2023) and consumer preferences (Van Loo et al. 2011). Compared to previous qualitative AMS surveys, DCE allows for quantitative examination of trade-offs between pecuniary and non-pecuniary benefits in scenarios that mirror actual investment situations. It helps reduce hypothetical and strategic biases, isolates individual attribute effects, and is generally considered more effective (Caputo & Lusk, 2020).

In the DCE, participants faced nine choice scenarios, each asking to choose to invest between two AMS options (A or B) with varying attributes, or to retain their current CMS (status-quo, option C). As only a few suppliers offer AMS with comparable prices and features, scenarios are framed with all AMS options come from a recognized brand with a 10-15 years expected lifespan, differing only in the attribute levels. An unlabeled design was employed to focus on labor benefits rather than brands or models.

Given the length constraints of mailed surveys and the cognitive burden of DCE tasks, to maintain a high response rate and attention, we focus on the most important attributes as detailed in Table 1[1]: *Price*, *Hired labor saving*, and *Owners' flexible time*, each with three levels comparable to those revealed in the market. A pilot study was conducted with stakeholders to ensure that the choice scenarios were realistic, relevant, and practical.

Figure 1 provides an example of how instructions, attributes, and a choice scenario were presented to the dairy farmers. To reduce the number of choice scenarios presented to each participant, the DCE was generated using a sequential Optimal Orthogonal-in-the-Differences design, resulting in nine choice scenarios per survey (Street, Burgess & Louviere, 2005). To minimize order effects, the sequence of choice scenarios was randomized. Additionally, a cheap talk script was included to mitigate hypothetical bias (Özdemir, Johnson, & Hauber, 2009). Each choice scenario included two questions: the uninduced question *"I would choose"* and the induced question *"Between A&B, I prefer."* The uninduced question allowed participants to make investing decisions on all three options while the induced question excluded the status quo option, forcing a choice between the two AMS options. For this study, only responses from the unforced choice are used to improve realism without external prompting.[2]

In addition to evaluating farmers' valuation for the pecuniary and non-pecuniary labor benefits, we also tested whether information regarding production influences potential adopters' decisions. We utilized a between-subject design, randomly distributing an equal number of surveys with and without additional information about a non-labor benefit: a 10% increase in milk production upon AMS adoption. The information is expected to lower the utility of staying with CMS if their adoption decisions are influenced by such non-labor benefit.

To investigate whether risk aversion affects potential adopters' preferences in technology adoption decisions, participants were asked a hypothetical question following Barsky et al. (1997), given a choice between receiving $1,000 without risk or a 50% chance to win $2,000 (and a 50% chance of receiving nothing). Those who chose a certain $1,000 were classified as risk-averse, while those who preferred to gamble or were indifferent were labeled as non-risk-averse. Similarly, to assess time-discounting preferences, we include a hypothetical question asking whether participants would prefer receiving $1,000 today or $1,500 next year, following Khwaja, Silverman & Sloan (2007). Those who opted for immediate payment were categorized as impatient. In the last part of the survey, participants' characteristics such as herd size, income source, confidence in future profitability, and experience with labor difficulties were recorded.

The [Blinded for Review] Institutional Review Board approved the study (IRB-FY2021-207). The power analysis based on the "T choices per parameter" rule (Assele, Meulders & Vandebroek, 2023) suggests a minimum sample size of 45 to identify each attribute. We mailed a six-page survey to a random representative sample of 1,000 dairy farmers currently using CMS in the region from November 2023 to March 2024[3]. We received a total of 316 responses, among which 212 were complete. Responses with missing answers were dropped, resulting in an effective response rate of 21.2%, which is average for mailed surveys with farmers (Pennings, Irwin & Good, 2002).

Table 2 provides an overview of the sample's characteristics, demonstrating a balanced response between the groups receiving surveys with and without the information regarding the non-labor benefit (i.e., milk production improvement of AMS adoption). Nationally, the average age of farmers is 58.1 years, and 35% have a college degree (USDA, 2024). In the dairy industry, approximately 74.2% of dairy farms have a herd size smaller than 100 (Njuki, 2022). In our survey with dairy farmers in the Midwest, 81% of farmers are aged 50 and above, 19% have a college degree, and 62% have a herd size smaller than 100. Overall, our sample is comparable to the national agriculture sector with fewer having a college degree.

Econometric Model

DCE is grounded in Lancaster's theory of consumer choice, which posits that consumption decisions are determined by the utility derived from the attributes of the goods consumed

(Lancaster, 1966). The econometric foundation of this approach relies on Random Utility Theory (RUM, McFadden, 1974). Within this framework, the utility that individual n derives from choosing alternative j in choice scenario t is represented as:

$$(1) \quad V_{njt} = \alpha_n Price_{njt} + \beta_{n1} Hired\ labor\ saving_{njt} + \beta_{n2} Owner's\ flexible\ time_{njt} + \beta_{n3} ASC_j + \beta_{n4} ASC_{info_{nj}} + \varepsilon_{njt}$$

where α_n is the marginal utility of price for individual n; $Price_{njt}$ represents the price of alternative j faced by individual n in choice scenario t; $Hired\ labor\ saving_{njt}$ and $Owner's\ flexible\ time_{njt}$ are continuous variables indicating the hired labor savings and additional owner's flexible time, respectively, associated with alternative j. ASC_j is an alternative-specific constant, taking the value 1 for the status quo option and 0 otherwise; ε_{njt} is the unobservable component, assumed to be Type I Extreme Value distributed.

Based on the separability of attribute effects in RUM and choice modeling theory (McFadden, 1974; Train, 2009), the information effect on production benefits should not influence the valuation of labor-related attributes but rather the overall alternative-specific constant ASC_j, which captures aspects of the status quo beyond labor benefits. Accordingly, ASC_info_{nj} is created as an interaction term of ASC_j and a dummy variable indicating whether the individual n received information about a 10% production improvement with AMS adoption (1 if received, 0 otherwise), thereby accounting for the potential information effect.

The DCE data were analyzed using a mixed logit (MXL) model to account for taste variation across individuals. Following previous literature (Espinosa-Goded, Barreiro-Hurlé & Ruto, 2010), the price coefficient α_n is assumed fixed, while coefficients β_n are specified as random variables following normal distributions. The model is estimated using simulated maximum likelihood estimation with 1,000 Halton draws, implemented via the *logitr* package in

R (Helveston, 2021). The marginal WTP for each attribute is calculated as $-\frac{\beta}{\alpha}$, and standard errors are estimated using the Delta method (Train, 2009). For direct interpretability, we also estimate the MXL model in the WTP space, following previous studies on consumer preferences (Hole & Kolstad, 2012). The units for the two attributes, *Hired labor saving* and *Owner's flexible time,* are presented as hours per week. To enhance interpretability, marginal WTP was estimated in dollars per week, and a discount factor was applied using a 4.68% interest rate (based on the 10-year U.S. Treasury rate as of April 2024), assuming a 12.5-year lifespan for AMS.

Previous qualitative AMS surveys have suggested that farm characteristics and stakeholders' sociodemographic profiles may affect AMS adoption (Peña-Lévano, Burney & Beaudry 2023; Lage et al. 2024). In our study, we explore preference heterogeneity on characteristics including herd size, income source, confidence in future profitability, experience with labor difficulties, risk aversion, and time discounting preferences.[4].

While the MXL model accounts for unobserved heterogeneity, it does not explain the sources (Boxall and Adamowicz ,2002). We employed four methods for robustness following previous literature, focusing on both estimated sample mean WTP and conditional individual WTP (which incorporates observed individual choices using Bayes' theorem): (1) interactions between individual characteristics and attributes and/or alternative-specific constants in the utility function, as proposed by McFadden and Train (2000), and applied in Brouwer, Martin-Ortega, and Berbel (2010); Kragt and Llewellyn (2014); Chèze, David, and Martinet (2020); (2) subsample analysis, which divide the whole sample into subsamples based on individual characteristics and compare model estimates across subsamples (Balcombe, Fraser & Falco, 2010; Lin, Nayga & Yang, 2024); (3) obtain the conditional individual WTP following Ishaq, Kolady & Grebitus (2023) and Lin, Nayga, and Yang (2024), and utilize ordinary least square

(OLS) along with (4) weighted least squares (WLS) regression on the estimated conditional individual WTP. A detailed explanation is presented in the Appendix IV.

Results

Whole Sample Analysis

Table 3 presents the estimated WTP from the MXL models in preference and WTP space. The consistency of estimated coefficients across both spaces indicates good model stability (Train 2009, Hole & Kolstad 2012). For interpretability, the WTP-space model is used for the following analysis.

As expected, the *Price* coefficient is negative and significant, confirming that higher investment reduces utility. Both *Hired labor saving* and *Owners' flexible time* show positive and strongly significant coefficients, underscoring the importance of both pecuniary and non-pecuniary labor benefits in AMS adoption. The interaction term for information *ASC_ info* is not statistically significant, implying that information about milk production gains does not significantly shift preferences away from the status quo.

On average, farmers are willing to pay \$3,150 for one hour of hired labor savings per week and \$6,827—2.17 times more—for one hour of additional owner flexible time per week, assuming a 10–15 years AMS lifespan. Applying a 4.68% discount rate over an average of 12.5 years, the discounted marginal WTP equates to \$6.37 per hour for hired labor savings and \$13.80 for the owner's flexible time. Standard deviations for *Hired labor saving* and *Owner's flexible time* are marginally significant ($0.05 < p < 0.1$), indicating modest heterogeneity in preferences

Heterogeneity Analysis

Table 4 summarizes heterogeneity in preferences for the pecuniary benefit of Hired Labor Saving and the non-pecuniary benefit of Owner's Flexible Time, assessed across four approaches:

interaction models, subsample analyses, and OLS and WLS regressions on conditional individual WTP. Detailed results are provided in the Appendix V and VI.

Among six characteristics evaluated, only two consistent findings emerge across methods: First, farmers who have experienced labor difficulties are likely to place a higher value on the pecuniary labor benefit Hired labor saving during AMS adoption. Second, farmers with secondary income sources are likely to show lower valuations for both labor benefits, a result that holds across all methods except the WLS model.

Discussion

This study provides key insights into technology adoption and how farmers value pecuniary and non-pecuniary labor benefits, and emphasizes the importance of recognizing and distinguishing non-pecuniary from pecuniary benefits. Traditional cost-benefit analyses often conclude that AMS adoption yields comparable or negative economic returns to CMS under certain management conditions (Rotz, Coiner & Soder, 2003; Bijl et al., 2007; Steeneveld et al., 2012; Shortall et al., 2016; Gargiulo et al., 2020). Our results suggest that gains from workload flexibility and improved well-being may be underestimated. Failure to account for these benefits may lead to an incomplete and inaccurate understanding and prediction of the adoption behavior and industry impact (Pannell and Claassen 2020). Future evaluations should incorporate non-pecuniary labor benefits to better inform decision-makers.

We find that providing information about improved production did not significantly affect farmers' AMS adoption decisions. Beyond the main model estimated on the total sample showing no information effect, we analyzed all subsamples divided by each characteristic in the subsample analysis (Appendix V) and found no information effect in any subgroup.[5] No information effects could be attributed to several factors. First, although previous surveys (Lage et al., 2024), noted that farmers consider production increase an important motivation for AMS adoption, our model suggests that participants may not view it as critical, instead focus primarily on labor-related benefits, as suggested by Michler et al. (2019). An alternative explanation is that: participants were already familiar with such information before receiving the survey, or they may not have paid sufficient attention to the information provided, resulting in no changes in their beliefs and therefore no observed effect on their choices (Grebitus, Roosen & Seitz, 2015). This explanation is supported by our survey findings indicating that participants who received the information about improved milk production with AMS adoption were not more likely to agree with the statement that AMS can improve milk production than those who did not receive it.

Consistent findings on preference heterogeneity align with expectations. It is reasonable that farmers who have experienced labor difficulties value hired labor savings higher, as they may desire the labor security offered by technology adoption (Foster & Rosenzweig, 2010; Staccioli & Virgillito, 2020). Regarding income sources, farmers with secondary incomes may be less dependent on dairy farming, prioritize their time allocation to other businesses, and have established ways to balance multiple tasks and incomes, making them less likely to value the labor benefits from AMS. Alternatively, incorporating findings from Fernandez-Cornejo et al. (2007) on farmers' secondary income and opportunity cost, dairy farmers with secondary income may earn lower wage rates compared to dairy income, which drives down the valuation of AMS.

Despite previous literature suggesting that risk-averse and impatient decision-makers typically have a decreased likelihood of adoption (Holt & Laury, 2002; Barham et al., 2014; Barham et al., 2015; Brick & Visser, 2015; Falk et al., 2023), we did not find strong evidence that risk and time-discounting attitudes affect preferences. Potential reasons could include that the risk-averse and time-discounting questions were not incentivized and hypothetical bias may have affected responses (Özdemir, Johnson & Hauber, 2009).

When interpreting our findings, an important consideration is that the extent to which non-pecuniary labor benefits influence adoption may depend on the nature of technology, industry, and adopter. While the dairy industry and AMS provide an ideal context for investigating non-pecuniary labor benefits, our findings may not generalize to all technologies without accounting for their unique characteristics. Moreover, even the same technology in the same industry may offer different magnitudes of non-pecuniary labor benefits depending on adopters' characteristics. For instance, small family-owned dairy farms that rely on the owners for labor may derive greater non-pecuniary benefits from AMS adoption (Cogato et al. 2021; Peña-Lévano, Burney & Beaudry 2023; Lage et al. 2024). Conversely, larger farms that depend heavily on hired labor may see minimal gains in the manager's flexible time, with most labor benefits accruing from reduced hired labor costs (Rotz et al., 2003; Mathijs, 2004; Bijl et al., 2007; Steeneveld et al., 2012; Shortall et al., 2016; Gargiulo et al., 2020). In the latter case, the traditional approach of calculating hired labor cost savings by incorporating market wage rates multiplied by labor input differences may yield less bias, as the non-pecuniary labor benefit is minimal.

Conclusion and Implications

Labor benefits of technology can be categorized into pecuniary benefits and non-pecuniary benefits. We examined the WTP of potential adopters in the U.S. Midwest for pecuniary labor benefits of hired labor savings and non-pecuniary labor benefits of owners' flexible time in the context of AMS adoption. Using data from a mailed survey inducting a DCE involving 212 dairy farmers, we find that one hour of owner's flexible time is valued at $13.80, 2.17 times higher than the hired labor savings at $6.37.

Our study finds that measuring labor benefits by estimating labor cost savings (as differences in labor inputs) while overlooking non-pecuniary benefits may underestimate the economic value of technology adoption and yield a partial understanding of the adoption impact. While both pecuniary and non-pecuniary labor benefits are positively valued across characteristics, heterogeneity exists. The common methods used in literature may yield different results when examining such heterogeneity, and it is crucial to check the robustness of findings by using multiple approaches. In our study, results were robust only for two characteristics out of six. For instance, farmers who have experienced labor difficulties (44%) value hired labor savings consistently more than their counterparts, while farmers who have secondary income sources (47%) value both pecuniary and non-pecuniary labor benefits less.

These findings have important implications. First, they emphasize accounting for non-pecuniary labor benefits in future studies when estimating the value of labor benefits from technology adoption. Future research should explore the trade-offs between pecuniary and non-pecuniary labor benefits across different technologies and stakeholder characteristics. Policymakers and scholars should consider the value of non-pecuniary benefits and preference heterogeneity when predicting adoption and formulating policies to better serve stakeholders. Second, our results suggest that targeted promotion strategies may effectively encourage AMS adoption. Since non-pecuniary labor benefits are valued significantly higher than pecuniary benefits, promotion efforts could emphasize these non-pecuniary advantages. As heterogeneity exists, AMS may not be cost-effective for everyone. Communication strategies might focus on farmers who rely solely on dairy income by highlighting the overall labor benefits. Similarly, farmers who have experienced labor difficulties could be targeted by emphasizing the pecuniary labor benefits of hired labor savings and labor security. Tailoring marketing messages to specific farmer segments may increase adoption rates.

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[1] Other potentially relevant factors (model, features, barn and farm types, etc) were excluded to keep the DCE cognitively manageable for farmers. For example, maintenance cost represents a recurring payment and would require discounting to combine with the lump-sum investment, introducing complexity and potential bias (Savage & Waldman 2008; Galesic & Bosnjak 2009; Revilla & Ochoa 2017).

[2] The choice between uninduced and induced formats in DCE depends on survey objectives (Breffle & Rowe, 2002), though uninduced questions are generally preferred for enhancing realism by avoiding forced choices (Ortúzar & Willumsen, 2024). However, including a status quo option can trigger status quo bias (Samuelson & Zeckhauser, 1988) or the endowment effect (Kahneman, Knetsch & Thaler, 1991), where respondents disproportionately favor the current state. Given the low AMS adoption rate in the U.S., we included an induced version as a backup to assess conditional preferences if the uninduced format yielded limited variation (e.g., all respondents selecting the status quo). To minimize potential interference, the uninduced question was presented first. Literature suggests that responses to both formats are generally consistent and do not interfere with one another (Collins & Vossler, 2009). 60.6% of participants chose the status quo in uninduced questions, providing sufficient variation.

[3] We focus on farmers currently using CMS for several reasons. First, CMS users represent the vast majority of the regional dairy sector and constitute the primary pool of potential adopters (Becerra, 2020; Cogato et al., 2021). They therefore provide a more relevant sample for understanding widespread barriers and drivers of adoption. Second, CMS users' valuations of

AMS are ex-ante and unaffected by ex-post rationalizations or learning effects, which can bias perceptions toward overly positive assessments and inflated WTP. This distinction is especially important for policy-oriented research aimed at informing adoption decisions before they occur. Third, restricting the sample to potential adopters helps minimize self-selection bias, as current AMS users may have unobserved characteristics that limit generalizability. Finally, because our study aims to inform policies and stakeholder engagement around AMS adoption, understanding how potential adopters perceive both pecuniary and non-pecuniary benefits is critical for designing effective outreach and incentives. Compared to studies focusing solely on current adopters, our approach better captures ex-ante investment preferences, aligning with the DCE framework. Ultimately, we aim to answer the question: *"What drives the decision to adopt?"* rather than *"How do farmers evaluate the technology after adoption?"*

[4] Among the characteristics collected, age, education, and whether farmers work overtime had insufficient variation (less than 45 respondents belonged to a specific level) required by the power analysis, and were excluded for the heterogeneity analyses.

[5] The coefficient for *ASC_info* is not significant in all subsamples except for those who are confident about future profitability. Further inspection shows that the significance is driven by an unbalanced subsample that experienced labor difficulties. Among farmers who were confident and did not receive the information nudge, 65.9% had experienced labor difficulties. In contrast, for those who were confident and received the treatment, only 38.2% had not experienced labor difficulties. After including an interaction term of $ASC\_info * I_{labor\ difficulties}$ in the subsample for those who are confident about future profitability, the coefficient for *ASC_info* is no longer significant.

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Figure 1. DCE instructions, information and choice scenario example

Choice Scenarios (please read carefully)

Imagine investing in your **FIRST** milking robot. In the following Choice Scenarios, we will show you different models of milking robots. While all models come from a leading brand with excellent service and reliability, and last 10-15 years, they only differ by the **following attributes:**

Price	Lump-sum payment for purchasing and installing **one box of milking robot** that handles **60-70 cows** (payment does not include barn retrofit or construction).
Labor Savings	Reduction in hired employees (family or non-family)'s working time.
Owner's Flexible Time	Reduction in owner or manager's time in running the farm.

In each Choice Scenario: first, choose the milking robot model you would invest in. If neither model is preferred, select "Keep using CMS". Then, if the CMS option is no longer available, select which robot you would prefer between the two.

There are no right or wrong answers. Please approach each question with the mindset that you bear the cost of buying the robot in real life.

There are no right or wrong answers. Please approach each question with the mindset that you bear the cost of buying the robot in real life.

A milking robot may increase **milk yield by 10%**.

Choice Scenario 1			
Attribute	**Milking robot A**	**Milking robot B**	**Keep using CMS**
Price	$270,000	$170,000	
Labor savings	40 hours/week	30 hours/week	
Owner's flexible time	4 hours/week	6 hours/week	
I would choose	O Robot A	O Robot B	O Keep CMS
Between A&B, I prefer	O Robot A	O Robot B	

Note: Only group that receive production improvement information saw the last statement.

Table 1. DCE attributes and levels

Attributes	**Description**	**Levels**
Price	Lump-sum payment for purchasing and installing one box of milking robots that handles 60-70 cows (payment does not include barn retrofit or construction).	\$170,000 \$220,000 \$270,000
Labor Savings	Reduction in hired employees (family or non-family)'s working time.	30 hours/week 35 hours/week 40 hours/week
Owner's Flexible Time	Reduction in owner or manager's time in running the farm.	4 hours/week 6 hours/week 8 hours/week

Note: The attribute levels are determined by previous AMS literature (Salfer et al., 2017; Cogato et al., 2021), qualitative research (Peña-Lévano, Burney & Beaudry 2023), interviews with industry experts, dairy extension specialists, and dairy farmer representatives conducted in September 2023.

Table 2. Sample descriptive characteristics

Farmer characteristic	Overall, N = 212[1]	Not informed, N = 105[1]	Informed, N = 107[1]	*p*-value[2]
Age 50 and above	172 (81%)	84 (80%)	88 (82%)	0.7
College degree	40 (19%)	19 (18%)	21 (20%)	0.8
Herd size smaller than 100	131 (62%)	60 (57%)	71 (66%)	0.2
Secondary income source on farm	100 (47%)	48 (46%)	52 (49%)	0.7
Work overtime[3]	191 (90%)	94 (90%)	97 (91%)	0.8
Experienced labor difficulties in past 5 years	94 (44%)	53 (50%)	41 (38%)	0.075
Confident about future profitability	75 (35%)	41 (39%)	34 (32%)	0.3
Risk-averse	156 (74%)	79 (75%)	77 (72%)	0.6
Patient	154 (73%)	77 (73%)	77 (72%)	0.8

[1]The informed group receives information about 10% production improvement with AMS adoption.

[2]Pearson's Chi-squared test.

[3]Respondents are labeled as working overtime if they work more than 40 hours per week. This is comparable to the national average working time for dairy farmers, which is 64 hours per week on the farm (USDA ERS, 2016).

Table 3. Mixed logit model in preference and WTP space on total sample

	MXL-preference space		MXL-WTP space	
Variable	Coeff.	SE	Coeff.	SE
Mean				
Price[a]	-0.026***	0.002	-0.026***	0.002
Hired labor saving[c]	3.123***	0.577	3.150***	0.575
Owner's flexible time	6.770***	1.483	6.827***	1.465
ASC	63.321*	35.588	71.997*	38.646
ASC_info	41.114	37.839	28.482	47.238
Standard deviation				
Hired labor saving	1.337**	0.608	1.190*	0.719
Owner's flexible time	4.756**	2.305	4.366*	2.491
ASC	396.877***	60.462	417.014***	63.914
ASC_info	206.179***	42.565	107.082**	50.049
Log likelihood	-764.839		-765.218	
AIC	1547.677		1548.437	
BIC	1597.661		1598.421	
R^2	0.635		0.635	

[a] For better comparison with models in preference space, the reported price parameter of models in WTP space is $-\lambda_n$.
[b] *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.
[c] The unit of estimated WTP is $1000; the unit of hired labor saving and owner's flexible time is hour per week.

Table 4. Results comparison of heterogeneity analyses on characteristics

Characteristics	Sample mean WTP analyses				Conditional Individual WTP analyses			
	Model with interaction		Subsample analysis		OLS model		WLS model	
	Hired labor saving	*Owner's flexible time*	*Hired labor saving*	*Owner's flexible time*	*Hired labor saving*	*Owner's flexible time*	*Hired labor saving*	*Owner's flexible time*
Small herd size			-				-	
Secondary income	-	-	-	-	-	-		
Confident on future profitability	+	+	+	+				
Experienced labor difficulties	+		+		+	+	+	
Risk averse					+			
Patient								

Note: + indicates a positive correlation, while – indicates a negative correlation, found between characteristic and the corresponding approach. As shown, characteristic of experienced labor difficulties on *Hired labor saving* is consistently positive across all methods while characteristic of secondary income on both benefits is consistenly negative across model with interaction, subsample analysis and OLS model.