J. Dairy Sci. 105
https://doi.org/10.3168/jds.2021-21216

Estimating the effect of different work practices and technologies on labor efficiency within pasture-based dairy systems

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ABSTRACT

Herd size expansion combined with the seasonal workload on pasture-based dairy farms has led to an increased focus on techniques that can improve farm labor efficiency such as work practices and technologies. The objective of this study was to identify the work practices and technologies associated with labor efficiency of particular tasks, and estimate the time savings that could be made through their implementation during the period of peak labor input on spring-calving dairy farms. Data from an existing labor time-use study, completed from February 1 to June 30, 2019 (150 d), on 76 Irish dairy farms was used in conjunction with a survey on work practice and technology implementation. One hundred ten work practices and technologies were included in the initial survey, and of these, 59 were found to have an association with labor efficiency for their respective tasks. Best practice, regarding labor efficiency, was identified for the 59 work practices and technologies. An accumulation score was compiled for work practice and technology implementation; each farm received one point for each work practice or technology implemented. On average, farms implemented 31 labor-efficient work practices and technologies (ranging from 10–45). The most labor-efficient 25% of farms implemented a greater number of work practices and technologies (n = 37) than the least labor-efficient 25% of farms (n = 25). Multiple regression models estimated that each additional work practice or technology implemented would improve farm labor efficiency by 0.6 h/cow. Additionally, backward-regression models were used to predict the labor-savings associated with the most important work practices and technologies. Labor-savings were estimated for 12 significant individual work practices and technologies, of which 5 were related to milking, 4 to calf care, 2 to cow care, and one to grassland management. The work practices and technologies that offered the largest labor-savings included having one person in the milking pit during the mid-lactation period (−3.04 h/cow), having automatic cluster removers present (−2.55 h/cow) and contracting slurry spreading (−1.78 h/cow). This study focused on the variety of labor-efficient work practices and technologies available and highlighted those that farmers should focus on to improve labor efficiency. The results indicated that there is scope for improvement in the adoption of labor-saving work practices and technologies on many farms. The positive effect of implementing the identified labor-saving techniques on labor efficiency could be used to support future adoption.

Key words: dairy farm labor, labor efficiency, work practice, technology

INTRODUCTION

Dairy industries in most Organization for Economic Co-operation and Development member countries have expanded in recent decades, leading to increased herd sizes and greater labor requirements (Barkema et al., 2015; Kelly et al., 2020). Concurrently, pasture-based dairy systems, operated in Ireland, New Zealand, and parts of Australia and Western Europe, continue to emphasize the importance of compact calving to maximize grass utilization and profitability (Roche et al., 2017). This practice of seasonal calving is associated with disproportionate labor demand throughout the year with Deming et al. (2018) showing that 57% of all labor input occurred in the spring and summer seasons on a subset of Irish dairy farms. These factors, together with traditional difficulties associated with the attraction and retention of labor in the dairy industry (Eastwood et al., 2020; Kelly et al., 2020), have led to labor efficiency and productivity becoming increasingly important regarding the management of dairy herds.

Labor efficiency on dairy farms is commonly represented in terms of hours worked per cow (O'Donovan et al., 2008; Wilson, 2011; Deming et al., 2018), which allows for comparison of labor efficiency among farms of

Received August 27, 2021.
Accepted February 10, 2022.
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differing scale. Other frequent measures include hours per full-time equivalent (**FTE**; Bewley et al., 2001; Edwards, 2018). However, the limitation of this metric is that the definition of an FTE can vary from farm to farm, and this could drive the wrong behavior if used incorrectly (i.e., increasing hours worked by the FTE will improve efficiency). To improve labor efficiency farmers are increasingly using labor-saving work practices and technologies (Deming et al., 2018; Yang et al., 2021). O'Brien et al. (2006) and Deming et al. (2018) identified several work practices (e.g., once-a-day milking in early lactation, group calf housing, and mechanical techniques to clean calf and calving facilities) associated with labor-efficient farms. However, these studies had limitations as the environment was restrained by milk quotas with smaller average herd sizes relative to 2021 (O'Brien et al., 2006) or were based on a limited sample of highly labor efficient farms (Deming et al., 2018). Apart from once-a-day milking (Edwards et al., 2020) and calf feeding practices (Gleeson et al., 2008), research on the potential of work practices to improve labor efficiency is limited.

Previous studies have identified the technologies that farmers are implementing to improve labor efficiency (Gargiulo et al., 2018; Dela Rue et al., 2020). Milking technologies, such as automatic cluster removers (**ACR**), automatic milk plant wash systems, in-parlor meal feeding, and automatic drafting, were the most prevalent technologies used on New Zealand and Australian dairy farms (Gargiulo et al., 2018; Dela Rue et al., 2020). Automatic calf feeders (Medrano-Galarza et al., 2017), automated heat detection (Steeneveld and Hogeveen, 2015), and smartphone apps to aid with herd management and decision support (Michels et al., 2019) are among the technologies being increasingly implemented for other farm tasks. Other studies have highlighted farmers' prepurchase considerations or the reasons why farmers invest in labor-saving technologies (Borchers and Bewley, 2015; Steeneveld and Hogeveen, 2015; Eastwood et al., 2016). In some cases, scenario modeling was used in an attempt to quantify the economic and labor-saving value of technologies, however, the effect of the technologies on labor demand was assumed (Tarrant and Armstrong, 2012; Edwards et al., 2014; Thomas et al., 2019). Survey results in New Zealand have indicated high levels of satisfaction on farms that have adopted automation technologies including ACR, automatic milk plant wash systems, in-parlor meal feeding, and automatic drafting, while also showing that these farms were more labor-efficient than peers without technology (Dela Rue et al., 2020). Similarly, other surveys have shown that farmers thought that they worked fewer hours since investing in technologies (Steeneveld and Hogeveen, 2015; Eastwood et al., 2016). However, these studies are subject to recall bias (Juster et al., 2003) as farmers retrospectively indicated their work hours. Confirmation bias may also be a factor, where farmers are recalling information to support their prior beliefs (Klayman, 1995), which could include justifying their investment through reduced work hours. As a result, the perceived benefits of technology are largely anecdotal (Eastwood et al., 2016; Hostiou et al., 2017) and actual time-use data showing how much time can be saved from individual or an accumulation of technologies is still required.

Large variations in labor efficiency from farm to farm indicate that the impact of work practices and technologies may affect individual farms differently (Deming et al., 2018). Additionally, there is an economy of scale effect to consider; as herd size increases, labor efficiency increases (Cournut et al., 2018; Deming et al., 2018). Consequently, it is difficult to quantify the specific effect of work practices and technologies on labor input, and to do so requires detailed information regarding both labor input as well as work practice and technology implementation. Therefore, the aim of this study was to (1) identify the work practices and technologies associated with dairy farm labor efficiency in the spring and summer seasons, and (2) estimate the potential improvements in labor efficiency achieved by implementing these labor-saving work practices and technologies.

MATERIALS AND METHODS

This study used 2 sources of data, which are detailed below: (1) farm time-use data were collected via a smartphone app and online survey; and (2) a survey was completed with each farmer involved in the study regarding the implementation of work practices and technologies. Approval for this study was granted by the Human Research Ethics Committee of University College Dublin, Ireland (LS-E-19-13-Hogan-Kinsella).

Time-Use Data Collection and Calculations

The time-use data used in this study formed part of a larger project examining labor efficiency on Irish dairy farms, the results of which can be found in Hogan et al. (2021). That study aimed to quantify labor input and efficiency on spring-calving dairy farms during the spring and summer seasons. As outlined in detail in Hogan et al. (2021), 82 farmers completed the time-use study between February 1 and June 30, 2019. This present study used only complete sets of farm labor input data (i.e., those with data recorded for each month), which included 76 farms. Selected farm characteristics are described in Table 1.

Table 1. Descriptive characteristics of farms included in the study, and averages and ranges in labor-efficient work practice and technology implementation (LEWPTI) score overall and per task for each herd size category for the study period [February 1 to June 30 (150 d)]

Item	Maximum score[1]	Herd size category[2] 1	2	3	4	Pooled SE	Average[3]	Range	P-value
Average herd size (cows)		72	115	178	285		137	50–394	
Average labor efficiency (h/cow)		26.3	17.7	14.3	10.9		18.2	7.2–47.9	
LEWPTI score									
Total	59	25.7^{a}	30.1^{b}	33.6^{bc}	39.1^{c}	1.41	30.9	10–45	<0.001
Milking	19	7.9^{a}	10.5^{b}	11.7^{b}	13.1^{b}	0.77	10.4	2–17	<0.001
Calf care	9	3.0^{a}	3.8^{ab}	4.6^{bc}	5.9^{c}	0.33	3.6	1–8	<0.001
Cow care	12	6.2	6.1	6.6	6.3	0.49	6.3	2–10	0.80
Grassland management	5	1.3^{a}	1.6^{a}	2.0^{ab}	3.0^{b}	0.34	1.8	0–5	0.02
Administration and business	2	0.8^{a}	1.2^{ab}	1.0^{ab}	1.7^{b}	0.19	1.1	0–2	0.04
Heifer care	3	1.1^{a}	1.3^{ab}	1.8^{bc}	2.4^{c}	0.21	1.5	0–3	<0.001
Feeding	5	3.7	3.7	3.4	3.7	0.19	3.8	2–5	0.93
General[4]	4	1.7	2.0	2.5	3.0	0.33	2.2	0–4	0.06

[a–c]Different superscripts indicate significant ($P < 0.02$) differences between herd size categories.

[1]The maximum score that could be obtained in each category.

[2]1 = farms with 50 to 90 cows (19 farms); 2 = farms with 91 to 139 cows (28 farms); 3 = farms with 140 to 239 cows (22 farms); and 4 = farms with ≥240 cows (7 farms).

[3]The average of all farms used in the analysis (n = 76).

[4]Variables that were not associated with a single task.

Farmers were nominated for the study by their Teagasc (Irish Agriculture and Food Development Authority) dairy farm adviser, and were selected based on having smartphone access and being a Teagasc client with dairy as their main farm enterprise. Farms were categorized into 4 herd size categories (**HSC**; 50–90 cows; 91–139 cows; 140–239 cows; and ≥240 cows) to ensure representation of a wide range of farm sizes. The categories with 50 to 90 cows and 91 to 139 cows represented 37 and 32% of the national dairy cow population, respectively (CSO, 2016). The categories with 140 to 239 cows (21%) and ≥240 cows (10%) accounted for the remaining 31%. These latter 2 categories were established because of the considerable variation in labor efficiency observed on farms with herd sizes >139 cows (Deming et al., 2018). Herds of less than 50 cows were excluded as they were less likely to be full-time specialist dairy farmers, and farms of this scale are declining in Ireland (CSO, 2013, 2016). This sampling strategy ensured a wide range of farm sizes and farms across all levels of labor efficiency. Farms were then selected to be proportionally represented within HSC and efforts were made to maximize the geographical distribution of farmers.

Data on time-use were collected using a smartphone app (developed by Acorn Agricultural Research). A description of the app, and its functionality are described in Deming et al. (2018) and Hogan et al. (2021). Briefly, the app's design allowed farmers to record their labor data in real time by starting and stopping a stopwatch function on the app as each designated task was commenced and completed. A list of the activities pertaining to each of the 10 tasks on the app are outlined in Table 2. Each farmer operated the app along with any staff or family members working on the farm with access to a smartphone. App users inputted their labor task data in real time during one (alternating) day each week (excluding Sundays to minimize the time impact and inconvenience on participants) between February 1 and June 30, 2019 (150 d). Other labor input by a person not using the app and hours of contractor work were captured through an online survey completed after each recording day. Following every recording day, data from the app and online survey were checked for errors. Where necessary, errors were corrected by the researcher following communication with the farmer.

Monthly task labor input was obtained by summing the duration of time spent at each individual task across each day of data input for the month for both app and online survey data (all breaks were excluded). This total was then divided by the number of recording days completed by the farmer for that month and multiplied by the total number of working days in the month. This calculation was based on farmers working 6 full

Table 2. Tasks on the smartphone app and their definitions

Task	Definition
Administration and business	Office work, advisory, staff management, sourcing materials, and trading dairy enterprise stock
Breaks	Breaks and nonfarm activities
Calf care	Preparing or transporting milk to calves, feeding milk or forage or supplement to calves preweaning, cleaning calf equipment, cleaning or bedding calf sheds, tagging, and veterinary work with calves
Cow care	Cubicle cleaning and bedding, cleaning yards and passages, veterinary (cows), heat observation and AI, and calving or monitoring cows
Feeding	Feeding forage and supplement to livestock other than preweaning calves, and silage management (e.g., removing pit covers, opening baled silage)
Grassland management	Grassland measurement, strip fencing, spraying, silage, reseeding, mowing, topping, and spreading fertilizer, lime, slurry, farmyard manure or soiled water
Heifer care	Herding, cubicle cleaning or bedding, cleaning yards or passages, veterinary, and heat observation and AI for heifers
Milking	Herding cows pre- or postmilking, washing postmilking, and milking
Other enterprises	Any other farm tasks not related to the dairy enterprise
Repairs and maintenance	Land and building maintenance, machinery maintenance, and milking machine maintenance

days per week and a half day on Sunday. A half day is based on the premise that 95% of the participating farmers indicated that they completed main tasks only on a Sunday. Total task labor input was obtained by summing the time spent at each task per month. Total labor input was calculated by summing each respective task labor input.

Average cow numbers were recorded through the online survey. Labor efficiency for the study period was measured as hours per cow, similar to previous studies (O'Donovan et al., 2008; Wilson, 2011; Deming et al., 2018). Labor efficiency was defined as hours per cow for the study period of February 1 to June 30 (150 d), equating to 21.4 weeks or 5 mo.

Work Practices and Technology Survey

The first or last author visited each farm to conduct a one-off survey, consisting of 110 questions relating to work practice and technology implementation. The survey incorporated questions related to all work practices and technologies implemented on the farm to determine which of these work practices and technologies were associated with labor efficiency. Work practices and technologies included in the survey were identified by previous studies (O'Donovan, 2008; Deming, 2018) and based on the knowledge of researchers based at Teagasc Moorepark Animal and Grassland Research and Innovation Centre, County Cork, Ireland.

Survey Analysis

Answers to questions were recorded in multiple classes and were grouped into binary responses (82 questions), or ternary responses (28 questions) when survey answers were compiled. Data were entered into SPSS 24 (IBM, 2016) along with the total and individual task labor efficiencies described above. Each work practice or technology was classified according to their associated farm task as defined in Table 2. Of the 110 work practices and technologies, 24 were associated with milking, 24 with cow care, 16 with calf care, 14 with grassland management, 11 with administration and business, 9 with general (work practices and technologies that were not associated with a single task), 8 with feeding, and 4 with heifer care. The eta squared (η^2) value, which measures the proportion of variation in the dependent variable that is associated with membership of different groups defined by the independent variable (Richardson, 2011), was calculated for each work practice or technology using the Compare Means function in SPSS with the labor efficiency of the particular task as the dependent variable. At this stage, 51 work practices and technologies with $\eta^2 < 0.01$ were excluded from the analysis based on the definitions of Cohen (1988), as there was no relationship with labor efficiency of the particular task observed. The remaining 59 work practices and technologies included in the subsequent analysis are presented in Appendix Table A1. For these 59 work practices and technologies, best practice was identified using the data available (Appendix Table A1) and the knowledge of researchers based at Teagasc Moorepark Animal and Grassland Research and Innovation Centre, Co. Cork. For each work practice or technology, a farm was allocated one point if they implemented best practice or zero points if they did not. A score for labor-efficient work practice and technology implementation (**LEWPTI**) was calculated for each task by summing the work practices and technologies included, and for each farm by summing the respective best practice scores.

Least squares means among HSC and labor efficiency ranking (assigned to quartiles using h/cow) were calculated using the general linear model function in SPSS.

The Tukey-Kramer multiple range test was used for mean separation ($P < 0.05$).

Model Development

A multiple regression model was created to estimate the effect of total LEWPTI score and herd size on-farm labor efficiency using the regression-linear function in SPSS with the following model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2,$$

where Y = total farm labor efficiency, β_0 = intercept, X_1 = total LEWPTI score, X_2 = herd size, and β_1 and β_2 were the respective partial regression coefficients.

Additionally, 7 multiple regression models [a model for each individual task that had an associated LEWPTI score (milking, calf care, cow care, grassland management, administration and business, heifer care, feeding)] were generated using the regression-linear function in SPSS. These models were created to identify the task LEWPTI scores that had an effect ($P < 0.05$) on the labor efficiency of that particular task. Where an effect was present, task LEWPTI scores for these tasks would be analyzed further to estimate the effects of individual work practices and technologies on the labor efficiency of that particular task. Labor efficiency of the particular task was included as the dependent variable with task LEWPTI score and herd size as explanatory variables:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2,$$

where Y = labor efficiency of particular task, β_0 = intercept, X_1 = task LEWPTI score, X_2 = herd size, and β_1 and β_2 are the respective partial regression coefficients.

Task LEWPTI score had an effect on labor efficiency of the particular task for 4 models (milking, calf care, cow care, grassland management; $P < 0.05$). The LEWPTI scores for each of these tasks were analyzed using a backward-elimination regression procedure to estimate the effects of significant ($P < 0.05$) individual work practices and technologies on labor efficiency of the particular task. As the work practices and technologies included in the LEWPTI scores were categorical variables, dummy variables were created through binary coding and a reference variable to which the dummy variables were compared. Any results obtained from these variables represent the difference between the dummy category and the reference category (Wooldridge, 2012). Only variables with $P < 0.05$ were retained in the final models. Multicollinearity among independent variables in all models was investigated (Montgomery et al., 2012) and found not to be a problem.

RESULTS

LEWPTI Scores

Of the 110 work practices and technologies included in the initial survey, 59 were associated ($\eta^2 \geq 0.01$) with labor efficiency for their respective tasks. Of the 59 work practices and technologies, 19 were associated with milking, 12 with cow care, 9 with calf care, 5 with grassland management, 5 with feeding, 4 with general, 3 with heifer care, and 2 with administration and business. The effect of HSC on LEWPTI scores is presented in Table 1. As HSC increased, farms implemented more labor-efficient work practices and technologies ($P < 0.001$) which can be attributed to the effects observed for the milking ($P < 0.001$), calf care ($P < 0.001$), grassland management ($P = 0.02$), administration and business ($P = 0.04$), and heifer care ($P < 0.001$) tasks. There were no differences among HSC for the cow care, feeding, and general LEWPTI scores.

The effect of labor efficiency quartiles on the total and individual task LEWPTI scores are presented in Table 3. The most labor-efficient 25% of farms implemented more labor-efficient practices and technologies than the least labor-efficient 25% of farms ($P < 0.001$), which can be attributed to the effects observed for the milking ($P < 0.001$), calf care ($P < 0.001$), grassland management ($P < 0.001$), heifer care ($P < 0.001$), and general scores ($P = 0.004$).

The multiple regression model estimating the effects of LEWPTI score and herd size on labor efficiency is presented in Table 4. The total LEWPTI score and herd size explained 54% of the variation in hours per cow. The analysis estimated that implementing one additional labor-efficient work practice or technology would improve labor efficiency by 0.60 h/cow. Each additional cow on the farm was associated with an improvement in labor efficiency of 0.03 h/cow.

The Effect of Individual Work Practices and Technologies on Labor Efficiency

Labor efficiency of particular tasks improved as task LEWPTI score increased for the milking ($P < 0.001$), calf care ($P = 0.006$), grassland management ($P = 0.004$), and cow care ($P = 0.004$) tasks. Therefore, 4 additional backward-regression models were developed to investigate the effects of individual work practices and technologies included in the milking, calf care, grassland management, and cow care LEWPTI scores on labor efficiency of those tasks.

Table 3. Average labor-efficient work practice and technology implementation (LEWPTI) score overall and per task for each labor efficiency quartile for the study period [February 1 to June 30 (150 d)]

LEWPTI task	Maximum score[1]	Labor efficiency ranking[2] 1	2	3	4	Pooled SE	P-value
Total	59	37.1[a]	31.9[b]	29.1[bc]	25.3[c]	1.16	<0.001
Milking	19	13.0[a]	10.8[ab]	10.2[b]	7.7[c]	0.64	<0.001
Calf care	9	4.5[a]	4.6[a]	4.0[ab]	2.9[b]	0.31	0.001
Cow care	12	6.6[ab]	7.3[a]	6.0[ab]	5.3[b]	0.39	0.004
Grassland management	5	2.9[a]	2.0[b]	1.3[bc]	0.8[c]	0.25	<0.001
Administration and business	2	1.2	1.1	1.2	0.9	0.17	0.50
Heifer care	3	2.0[a]	1.5[ab]	1.4[ab]	1.1[b]	0.19	0.008
Feeding	5	3.6	3.7	3.6	3.4	0.17	0.59
General[4]	4	2.8[a]	2.5[a]	2.0[ab]	1.4[b]	0.27	0.003

[a–c]Different superscripts indicate significant ($P < 0.008$) differences between labor efficiency quartiles.

[1]The maximum score that could be obtained in each category.

[2]Labour efficiency ranking based on h/cow for each task; 1 = most labor-efficient quartile (19 farms); 2 = upper mid quartile (19 farms); 3 = lower mid quartile (19 farms); and 4 = least labor-efficient quartile (19 farms).

[4]Variables that were not associated with a single task.

Five work practices and technologies had an effect on milking labor efficiency and were included in the final model, which had an R^2 value of 0.52 (Table 5). Four work practices and technologies had an effect on calf care labor efficiency and were included in the final model, which had an R^2 value of 0.27 (Table 6). The grassland management model had an R^2 of 0.30 with contracting slurry spreading the only work practice included (Table 7). Finally, 2 work practices were included in the final cow care model (Table 8) and the R^2 was 0.19.

DISCUSSION

Labor efficiency on dairy farms is influenced by a wide range of factors. This combined with large variation in labor efficiency between farms (Cournut et al., 2018; Deming et al., 2018) means it is difficult to estimate the effect of work practices and technologies on labor input. Evidence-based research is a key consideration for farmers when deciding to adopt new work practices and technologies (Borchers and Bewley, 2015), and there is a lack of evidence to-date of the time-saving potential of different labor-efficient work practices and technologies. Using detailed information regarding labor input, and work practice and technology implementation on 76 dairy farms, this study identified 12 key labor-efficient work practices and technologies (Tables 5 to 8) across the 4 most time-consuming farm tasks from February to June (Hogan et al., 2021), and estimated their potential labor-savings during the peak periods of workload for spring-calving dairy farms. Improved labor efficiency can enhance many key aspects of dairy farming including: reducing work hours (Deming et al., 2018), and improving health and safety for farm operators (Osborne et al., 2010); creating more attractive workplaces (Eastwood et al., 2020) and increasing farm profitability as influenced by labor costs (Hemme et al., 2014). Therefore, the results of this study can contribute positively to future social and economic sustainability of pasture-based dairy farms.

This study identified 59 work practices and technologies associated with labor efficiency of particular tasks, representing a wide variety of options for farms to improve labor efficiency through work practices and technologies. On average, farms implemented 31 work practices and technologies indicating scope for improvement, especially within HSC 1, with these farms implementing fewer work practices and technologies than the other HSC. To improve labor efficiency, farms should implement more labor-efficient work practices and technologies and this study showed that each additional work practice or technology implemented could potentially improve labor efficiency by 0.60 h/cow. Certain labor-efficient work practices and technologies (e.g., ACR, automatic calf feeders) require large capital expenditure and a cost-benefit appraisal may be necessary. However, many other techniques are low-cost requiring improved work organization (e.g., leaving the milking pit to herd cows into the parlor or leaving the

Table 4. Partial regression coefficients, SE, and P-values for the total regression model with labor-efficient work practice and technology implementation (LEWPTI) score and herd size included as fixed effects (number of records = 76), and labor efficiency (h/cow) for the study period [February 1 to June 30 (150 d)] as the dependent variable ($R^2 = 0.54$)

Independent variable	Partial regression coefficient (95% CI)	SE	P-value
Intercept	41.51 (35.43, 47.60)	3.05	<0.001
Total LEWPTI score	−0.60 (−0.85, −0.35)	0.13	<0.001
Herd size	−0.03 (−0.06, −0.01)	0.01	0.009

Table 5. Variables, partial regression coefficients, SE, and *P*-values associated with the final milking labor efficiency model with h/cow for milking for the study period [February 1 to June 30 (150 d)] as the dependent variable (number of records = 76; $R^2 = 0.49$)

Variable	Partial regression coefficient (95% CI)	SE	*P*-value
Intercept	11.92 (10.05, 13.80)	0.94	<0.001
One person in the milking pit during the mid-lactation period	−3.04 (−4.28, −1.79)	0.63	<0.001
Does not leave the milking pit to feed calves during milking	−1.31 (−2.41, −0.22)	0.55	0.02
Using a quad/jeep when herding cows to and from the milking parlor	−0.87 (−1.73, −0.002)	0.43	0.05
Automatic cluster removers present	−2.55 (−3.45, −1.65)	0.45	<0.001
Cow exit gates can be operated from anywhere in the milking pit	−0.94 (−1.85, −0.02)	0.46	0.05

milking pit to feed calves during milking), which could have large effects on labor efficiency through the elimination of unnecessary work (Snee, 2010). Therefore, work organization methods could be the first focus for farmers as they may be relatively easier to implement than other high cost technologies.

Milking is the most time-consuming task on dairy farms accounting for between 33 and 57% of labor input in pasture-based dairy systems (O'Donovan et al., 2008; Taylor et al., 2009; Deming et al., 2018). As a result, several studies have identified different approaches to improve milking efficiency including milking parlor capacity and milking routine (O'Brien et al., 2012), and labor-saving technologies (Dela Rue et al., 2020; Edwards et al., 2020). This study included all possible labor-saving work practices and technologies for milking; identifying 19 labor-efficient work practices and technologies and estimating the time savings for the 5 significant work practices and technologies (Table 5). Four of these techniques focused on improved work organization or streamlined work processes (one person in the milking pit during the mid-lactation period, the operator not leaving the milking pit to feed calves during milking, using a quad or jeep when going to herd cows to and from the milking parlor, and being able to operate cow exit gates from anywhere in the milking pit), which integrated Lean management principles to remove unnecessary work (George and Tamilio, 2012). Lean management represents a business management approach that focuses on continuous improvement, making incremental changes in processes to improve work quality and efficiency (Womack et al., 2007). "Lean" farmers have been shown to be more labor-efficient at milking than farmers not using these principles (Beecher et al., 2021). Ease of implementation is a consideration for farmers when adopting new techniques (Borchers and Bewley, 2015). Therefore, the 4 practices highlighted above, which should be relatively easy to implement, should be a key focus for farms to improve milking labor efficiency if not already implemented.

Having one milking parlor operator during mid-lactation offered the greatest time-saving of 3.04 h/cow, followed by ACR at 2.55 h/cow. Having one milking operator may not be possible in all milking parlors, and is contingent on having good cow flow and milking routine, and ACR to manage larger parlors of up to 30 units (O'Brien et al., 2012). Achieving a balance between operator comfort and milking efficiency is important where there is one milking operator, particularly to attract hired labor (Porter, 1993). The ACR can assist with this, generally purchased to improve labor efficiency and operator comfort (Eastwood et al., 2016). Tarrant and Armstrong (2012) found that ACR removed laborious work from the milking process, making the milking task less labor intensive and decreasing the risk of repetitive strain injuries for the operator. Previous research has highlighted the significant improvements in labor efficiency on farms with ACR compared with those without them (Edwards et al., 2020). It is likely that reducing the number of workers in the milking pit is where ACR have the greatest potential to improve labor efficiency, as highlighted by Dela Rue et al. (2020) in the case of rotary parlors. Over-milking of cows is prevented when ACR are present, allowing

Table 6. Variable, partial regression coefficients, SE, and *P*-values associated with the final calf care labor efficiency model with h/cow for calf care for the study period [February 1 to June 30 (150 d)] as the dependent variable (number of records = 76; $R^2 = 0.27$)

Variable	Partial regression coefficient (95% CI)	SE	*P*-value
Intercept	3.44 (2.92, 3.97)	0.26	<0.001
Calves trained on group feeders (d 1–4)	−0.52 (−1.01, −0.04)	0.24	0.04
Using automated or ad libitum calf feeding methods once trained	−0.71 (−1.31, −0.12)	0.30	0.02
Not rearing bull calves on farm	−0.69 (−1.24, −0.14)	0.28	0.01
Contract calf rearing before weaning	−0.79 (−1.52, −0.06)	0.37	0.03

Table 7. Variable, partial regression coefficients, SE and *P*-values associated with the final grassland management labor efficiency model with h/cow for grassland management for the study period [February 1 to June 30 (150 d)] as the dependent variable (number of records = 76; $R^2 = 0.30$)

Variable	Partial regression coefficient (95% CI)	SE	*P*-value
Intercept	3.40 (2.95, 3.85)	0.23	<0.001
Contracted slurry spreading	−1.78 (−2.41, −1.15)	0.32	<0.001

the operator to manage more clusters (Edwards et al., 2013). Studies have noted that it can be difficult to justify investment in ACR in herringbone parlors where the milking operator must still swing over the cluster from the middle of the pit (Edwards et al., 2020); however, Tarrant and Armstrong (2012) found that the investment was justified in parlors with more than 15 units. These studies were based on scenario modeling (Tarrant and Armstrong, 2012; Edwards et al., 2020), and consequently, more research is needed to understand the farm situations that will gain the greatest benefit from implementing this technology.

Calf care accounted for 13% of all labor input from February to June but consumed a greater proportion of time (20%) in the peak months of labor input in February and March for pasture-based systems (Hogan et al., 2021). However, this study identified that contract rearing calves preweaning and selling male calves can significantly reduce the time input (1.5 h/cow) spent at calf care. Contract rearing is an increasingly popular practice on farms to improve the utilization of land, labor, and facilities (Olynk and Wolf, 2010), allowing farmers to offset a proportion of the labor associated with calf rearing. There is an economic cost to the farmer regarding this practice as the labor input is contracted to another farmer, and that contracted labor input is not accounted for in this study. However, Deming et al. (2019) has shown that contracting calf rearing does not have a significant negative impact on farm profitability. The sale of male calves can reduce the number of farm enterprises to manage. Similarly, other studies have documented that specialist dairy farmers (reducing multiple farm enterprises) have higher levels of profitability and labor efficiency (Wilson, 2011; Kelly et al., 2013).

When calves are reared on farm, automated calf feeders and training calves on group feeders were estimated to offer significant labor-savings of 0.71 and 0.52 h/cow, respectively. Automated calf feeders are an increasingly prominent technique to improve calf care labor efficiency (Medrano-Galarza et al., 2017). Sinnott et al. (2021) showed that automated calf feeders saved over 1 min/calf per day when compared with conventional teat feeding systems. This facility also allows the flexibility of being able to check on calves at a time convenient to the farmer as opposed to a designated feeding time (Palczynski et al., 2020). However, the large investment required can be an adoption barrier on some farms (Palczynski et al., 2020), and further research regarding the cost-benefit of these machines is required. Similar to this study, Deming et al. (2018) found that training calves in group pens was associated with the most labor-efficient farms. This practice can reduce the manual labor associated with cleaning and managing individual pens and feeders. Using the 4 labor-saving techniques highlighted through the backward regression, farmers could eliminate a large proportion of the time spent at the calf care task so the uptake of these techniques should be encouraged.

Of the 5 labor-efficient work practices and technologies identified for grassland management, 3 were related to greater use of contractors for slurry, fertilizer, and soiled water spreading. At 1.70 h/cow, using contractors for slurry spreading offered the greatest labor-saving for this task. Contractors are increasingly used by farmers as they can allow for efficient completion of farm tasks without the need for extra staff or farm machinery (Nye, 2018). Deming et al. (2019) showed that contracting machinery work (including fertilizer and slurry spreading) would not have a large negative effect on farm profitability. Usually, contractors have more efficient equipment which reduces the time spent at tasks, so their use, particularly in spring, can save time (Deming et al., 2019) and allow farmers to allocate labor to other tasks.

In general, labor-saving ideas for the cow care task have not been identified by previous literature, despite

Table 8. Variable, partial regression coefficients, SE, and *P*-values associated with the final cow care labor efficiency model with h/cow for cow care for the study period [February 1 to June 30 (150 d)] as the dependent variable (number of records = 76; $R^2 = 0.19$)

Variable	Partial regression coefficient (95% CI)	SE	*P*-value
Intercept	2.17 (1.88, 2.46)	0.15	<0.001
Cleaning dry cow cubicles once per day	−0.49 (−0.81, −0.17)	0.16	0.003
No hand scraping taking place	−0.45 (−0.76, −0.13)	0.16	0.006

it consuming 11% of total labor input during calving and breeding periods (Hogan et al., 2021). One technology that has been identified for its time-saving potential is automated heat detection (Adenuga et al., 2020), and this was one of the 12 work practices and technologies highlighted in this study for cow care. Of the 12 work practices or technologies, bedding cubicles once per day and eliminating yard scraping by hand were significant in the cow care backward regression and were estimated to save 0.49 and 0.45 h/cow respectively. These practices, similar to many others in the study (e.g., not transferring milk to the calf house in buckets, pushing in silage mechanically), involve reducing manual work on the farm, which will be important to attract and retain future farm workers (Beecher et al., 2019) and improve safety and wellbeing in farm workplaces (Osborne et al., 2010).

Herd Size Effect

The economy of scale effect regarding labor efficiency (as herd size increases, labor efficiency improves) has been emphasized in many studies (Cournut et al., 2018; Deming et al., 2018) and the findings from the present study corroborates this. Increased implementation of labor-efficient work practices and technologies represents one option by which smaller scaled farms can improve labor efficiency relative to larger farms. It is possible that there are cost barriers for some technologies (e.g., automatic calf feeders), and that the full labor-saving benefits will not be seen on smaller farms [i.e., investment in ACR in parlors of less than 15 units can be hard to justify (Tarrant and Armstrong, 2012)]. There was no difference in LEWPTI score among HSC for cow care, and feeding, suggesting that regardless of herd size, farms used similar labor-efficient work practices and technologies to complete these tasks. This would suggest that larger farms are using different techniques that were outside the scope of this study, such as better facilities and larger machinery to increase efficiency for these tasks.

Reflection on Research Method, Limitations, and Future Research

The novel aspect of this study was the holistic approach to identify, and then estimate the effects of labor-saving work practices and technologies on labor efficiency using an accumulation technique (LEWPTI score). Whereas, some studies hand-picked a selection of work practices or technologies implemented on the most labor-efficient farms (O'Brien et al., 2006; Deming et al., 2018), this study incorporated all work practices and technologies before removing those not associated with labor efficiency. This removed any potential bias regarding the selection of labor-efficient work practices and technologies. Measuring the effect of work practices and technologies on farm performance is often a challenge for researchers as farms that have adopted one work practice or technology are more likely to have adopted others, leading to upward bias when measuring the effect on the farm system (Khanal et al., 2010). Including all labor-efficient work practices and technologies and then using an accumulation score to measure the effects of work practices and technologies overcame this challenge.

Performance measurement has become a key part of business success (Neely, 1999). The LEWPTI scores, as a checklist, could be used to measure performance in relation to labor-efficient work practice and technology implementation. Farmers and farm advisers could use this checklist to encourage the uptake of labor-efficient work practices and technologies, as well as identify areas where labor efficiency improvements can be made on farms. In other industries, the use of similar checklists has improved performance outcomes, and can allow the user to refocus on activities that may have otherwise gone unnoticed (Hales and Pronovost, 2006).

This study used regression models to estimate the effects of labor-efficient work practices and technologies on labor efficiency. As dairy farms vary hugely in terms of management skill and resources, work practices and technologies will be adopted differently on each individual farm, resulting in variable effects on the farm system (Brotzman et al., 2015). Accordingly, the estimations used in this study should be interpreted as such, and taken as a guide only. Future studies in more controlled environments will be necessary to ascertain the benefits of individual work practices and technologies at an individual farm level. The present study uses data from only part of the year (February 1 to June 30) that is the calving and breeding period for spring-calving Irish dairy herds, so the effects of labor-saving work practices and technologies may differ over a full year.

Future research will be necessary to ascertain the economic impact of adopting labor-efficient technologies that require substantial investment (e.g., automated calf feeders, ACR). This is important as farmers' pre-adoption considerations relate to cost-benefit and investments costs (Borchers and Bewley, 2015).

CONCLUSIONS

Results from this study have emphasized the potential of work practices and technologies to improve labor efficiency. A wide range of labor-efficient work practices and technologies are available to dairy farmers and when accumulated they can have a significant impact on farm labor efficiency. There is scope for improvement in the adoption of these work practices and technologies with the average farm LEWPTI score of 31, however, the benefits of implementing labor-efficient work practices and technologies are now evident. Labor-savings were estimated for the 12 most important work practices and technologies across the milking, calf care, cow care, and grassland management tasks, and implementing these 12 techniques could be the first focus for farmers attempting to improve labor efficiency. These estimations offer an insight into the labor-saving benefits of labor-efficient work practices and technologies using real-time on-farm data, and should reassure farmers of their benefits and ensure a greater level of future adoption. Finally, future studies will be necessary to understand the cost-benefit of many of these work practices and technologies, particularly high cost technologies.

ACKNOWLEDGMENTS

The authors acknowledge the farmers that participated in the collection of data and their cooperation. This work was supported by Dairy Research Ireland (Merrion Square, Dublin, Ireland; MKLS0369). The authors have not stated any conflicts of interest.

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APPENDIX

Table A1. Survey questions that were associated with labor efficiency of particular tasks ($\eta^2 > 0.01$) and included in the labor-efficient work practice and technology implementation (LEWPTI) scores

Variable	Mean labor efficiency of particular task	Frequency[1] (n)	SD	η^2
Milking[2]				
Is once-a-day milking practiced in early lactation?				
Yes[3]	4.58	24	1.53	0.08
No	6.06	52	2.67	
How many people are present in the milking pit during the mid-lactation period?				
One[3]	5.32	65	2.00	0.08
More than one	7.22	11	4.05	
Does the milking operator leave the milking pit to herd cows into the parlor?				
Yes	6.95	18	3.47	0.10
No[3]	5.17	58	1.90	
Does the milking operator leave the milking pit to feed calves during milking?				
Yes	6.33	14	2.61	0.02
No[3]	5.43	62	2.42	
Are there cow-handling facilities beside the milking parlor?				
Yes[3]	5.46	72	2.39	0.06
No	8.06	4	2.82	
Are there cow-drafting facilities present?				
Yes[3]	4.90	47	1.62	0.13
No	6.73	29	3.12	
Does premilking teat preparation take place?				
Yes	6.13	33	2.70	0.04
No[3]	5.18	43	2.20	
Is postmilking teat disinfection practiced?				
Drop-down sprayers[3]	5.15	53	1.93	0.08
Hand sprayers, cups, or other	6.63	23	3.20	
How are cows normally herded to and from the parlor for milking?				
Walking	6.00	32	3.02	0.02
Quad or jeep[3]	5.30	44	1.93	
Can cows go directly to the paddock after every milking?				
Yes[3]	4.97	39	1.63	0.07
No	6.25	37	2.99	
Are there automatic cluster removers present?				
Yes[3]	4.61	46	1.53	0.25
No	7.11	30	2.84	
Is there a dumpline present?				
Yes[3]	4.74	24	1.56	0.06
No	5.99	52	2.70	
What type of meal feeders are in the milking parlor?				
Automatic[3]	6.61	22	3.32	0.07
Manual, semi-automatic, or none	5.18	54	1.89	
Can cow exit gates be operated from anywhere in the milking pit?				
Yes[3]	5.04	50	1.72	0.1
No	6.67	26	3.25	
Can cow entry gates be operated from anywhere in the milking pit?				
Yes[3]	4.70	19	1.71	0.05
No	5.89	57	2.61	
Can cows walk straight out of the milking parlor?				
Yes or greater than 2.5 m to wall[3]	4.94	45	1.61	0.1
No, wall less than or equal to 2.5 m	6.54	31	3.12	
Is there an automatic plant wash present?				
Yes[3]	4.90	16	2.09	0.02
No	5.78	60	2.53	
Is there an automatic backing gate present?				
Yes[3]	4.76	9	2.68	0.02
No	5.71	67	2.43	
How many rows of cows?				
<9[3]	5.52	23	2.02	0.02

Continued

Table A1 (Continued). Survey questions that were associated with labor efficiency of particular tasks ($\eta^2 > 0.01$) and included in the labor-efficient work practice and technology implementation (LEWPTI) scores

Variable	Mean labor efficiency of particular task	Frequency[1] (n)	SD	η^2
9 to 13	5.88	37	2.83	
>13	5.06	16	2.13	
Calf care[4]				
How is fresh milk transported to the calf house?				
Buckets	2.20	26	0.83	0.02
Piped directly or mechanically[3]	2.52	50	1.33	
How are calves initially trained from d 1–4?				
Group feeder[3]	2.20	42	0.98	0.08
Individual feeder	2.76	32	1.36	
Robot	1.27	2	0.62	
How are calves fed once trained and grouped?				
Robot or ad libitum[3]	1.84	16	0.62	0.06
Group feeder	2.56	60	1.26	
How often are calf pens bedded?				
Daily	2.60	23	1.27	0.01
Every second day[3]	2.27	30	1.12	
Less than every second day	2.41	23	1.21	
How often are calf pens cleaned?				
Weekly or greater[3]	2.33	19	1.03	0.01
Less than weekly	2.33	36	0.99	
Annually	2.63	21	1.59	
Is the calf facility purpose built?				
Yes[3]	2.27	33	1.01	0.01
No	2.52	43	1.30	
Are bull calves reared on farm?				
Yes or keeps some	3.06	22	1.07	0.13
No[3]	2.14	54	1.14	
At what age are most bull calves sold?				
≤3 wk[3]	2.22	51	1.20	0.05
>3 wk	2.79	25	1.09	
Are any heifers contract reared preweaning?				
Yes[3]	1.50	10	0.73	0.09
No	2.55	66	1.19	
Cow care[5]				
How are dry cows housed at the point of calving?				
Individual pens	2.02	20	0.93	0.07
Group pens or combination[3]	1.58	56	0.61	
How often is the calving facility cleaned?				
Weekly or greater[3]	1.59	26	0.66	0.01
Monthly or greater but less than weekly	1.79	28	0.70	
Less than monthly	1.69	22	0.84	
How long do cows stay in the calving area?				
<24 h	1.78	41	0.81	0.02
24–48 h[3]	1.52	11	0.62	
>48 h	1.62	24	0.63	
What heat detection aids are used?				
Tail paint or vasectomized bull	1.74	64	0.75	0.03
Automated heat detection[3]	1.36	9	0.50	
No heat detection aids	1.69	3	0.91	
Is once or twice a day AI practiced?				
Once[3]	1.62	45	0.74	0.01
Twice	1.77	30	0.71	
How often are milking cow cubicles cleaned?				
Twice daily[3]	1.77	52	0.72	0.03
Once daily or less	1.52	24	0.73	
How often are dry cow cubicles cleaned?				
Twice daily	2.19	15	0.82	0.12
Once daily or less[3]	1.54	49	0.63	
Never	1.71	12	0.77	
How often are milking cow cubicles bedded?				

Continued

Table A1 (Continued). Survey questions that were associated with labor efficiency of particular tasks ($\eta^2 > 0.01$) and included in the labor-efficient work practice and technology implementation (LEWPTI) scores

Variable	Mean labor efficiency of particular task	Frequency[1] (n)	SD	η^2
Twice daily[3]	1.76	51	0.72	0.02
Once daily or less	1.56	25	0.73	
How often are dry cow cubicles bedded?				
Twice daily	2.25	13	0.84	0.13
Once daily or less[3]	1.54	48	0.61	
Never	1.70	15	0.80	
Does hand scraping take place?				
Yes	1.86	46	0.80	0.08
No[3]	1.43	30	0.50	
Are all cows housed in the same shed?				
Yes[3]	1.56	38	0.72	0.03
No	1.83	38	0.72	
Are any cow passages hand or tractor scrapped?				
Yes	1.92	12	0.79	0.02
No[3]	1.65	64	0.71	
Grassland management[6]				
Is strip fencing used after the first rotation?				
Yes	2.72	32	1.76	0.02
No[3]	2.16	27	1.74	
When grazing conditions are difficult	2.56	17	1.15	
On what date were cows turned out full time?				
Before February 14[3]	2.33	37	1.85	0.01
February 14–28	2.81	17	1.72	
On or after March 1	2.49	22	1.12	
Who spreads the farm fertilizer?				
Farmer or farm staff	3.06	48	1.73	0.24
Contractors[3]	0.58	5	0.21	
Combination	1.68	23	0.72	
Who spreads the farm slurry?				
Farmer or farm staff	3.46	16	1.99	0.3
Contractors[3]	1.62	39	0.82	
Combination	3.35	21	1.66	
Who spreads the soiled water?				
Farmer or farm staff	2.90	45	1.62	0.17
Contractors[3]	1.57	26	0.96	
Combination	2.40	4	1.28	
Administration and business[7]				
When is farm office work usually undertaken?				
Morning[3]	1.41	31	1.11	0.02
Afternoon or evening	1.34	27	0.67	
No specific time allocated	1.71	18	1.53	
How many days per week is office work typically undertaken?				
More than once a week[3]	1.34	52	0.99	0.03
Less than once a week	1.72	24	1.29	
Heifer care[8]				
Are any heifers contract reared?				
Yes[3]	0.24	17	0.22	0.18
No	0.69	59	0.44	
How are maiden heifers bred?				
AI	0.79	12	0.51	0.1
Natural service	0.30	11	0.27	
AI and natural[3]	0.60	53	0.43	
What is the length of the AI period for heifers?				
≤3 wk[3]	0.45	43	0.41	0.13
>3 wk	0.77	33	0.42	
Feeding[9]				
What machinery is used to feed cows?				
Tractor + grab or loader[3]	0.57	62	0.43	0.04
Contracted	0.12	1		
Diet feeder	0.75	13	0.52	

Continued

Table A1 (Continued). Survey questions that were associated with labor efficiency of particular tasks ($\eta^2 > 0.01$) and included in the labor-efficient work practice and technology implementation (LEWPTI) scores

Variable	Mean labor efficiency of particular task	Frequency[1] (n)	SD	η^2
Are any stock outwintered?				
Yes	0.73	13	0.39	0.02
No[3]	0.57	63	0.46	
Is silage pushed in between fresh feeds?				
No or mechanically[3]	0.55	67	0.32	0.08
Yes, manually or combination	0.93	9	0.95	
How much feed space is available per cow?				
≤0.3 m	0.27	4	0.21	0.03
>0.3 m[3]	0.61	72	0.46	
Is there waste silage to be removed from the feed area?				
Yes	0.58	66	0.43	0.02
No[3]	0.74	10	0.59	
General[10]				
Do you travel to an outside block each day?				
Yes	20.95	34	7.94	0.1
No[3]	16.06	42	6.89	
Do you have other enterprises on farm?				
Yes	20.86	24	8.63	0.05
No[3]	17.04	52	7.04	
Do you take any time off between the start of calving and end of breeding?				
Yes[3]	16.03	43	5.71	0.11
No	21.14	33	9.05	
Do you use standard operating procedures?				
Yes[3]	16.13	27	7.56	0.04
No	19.42	49	7.65	

[1]n = 76.

[2]Mean labor efficiency for milking = 5.59 h/cow; SD = 2.46 h/cow.

[3]Best practice for labor efficiency.

[4]Mean labor efficiency for calf care = 2.41 h/cow; (SD) = 1.19 h/cow;

[5]Mean labor efficiency for cow care = 1.69 h/cow (SD = 0.73 h/cow);

[6]Mean labor efficiency for grassland management = 2.48 h/cow (SD = 1.63 h/cow);

[7]Mean labor efficiency for administration and business = 1.46 h/cow (SD = 1.10 h/cow);

[8]Mean labor efficiency for heifer care = 0.59 h/cow (SD = 0.44 h/cow);

[9]Mean labor efficiency for feeding = 0.60 h/cow; (SD = 0.45 h/cow);

[10]Mean labor efficiency for general = 18.25 h/cow; (SD = 7.73 h/cow).