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# Factors associated with intensity of technology adoption and with the adoption of 4 clusters of precision livestock farming technologies in Irish pasture-based dairy systems

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## ABSTRACT

Precision livestock farming (PLF) technologies have been widely promoted as important tools to improve the sustainability of dairy systems due to perceived economic, social, and environmental benefits. However, there is still limited information about the level of adoption of PLF technologies (percentage of farms with a PLF technology) and the factors (farm and farmer characteristics) associated with PLF technology adoption in pasture-based dairy systems. The current research aimed to address this knowledge gap by using a representative survey of Irish pasture-based dairy farms from 2018. First, we established the levels of adoption of 9 PLF technologies (individual cow activity sensors, rising plate meters, automatic washers, automatic cluster removers, automatic calf feeders, automatic parlor feeders, automatic drafting gates, milk meters, and a grassland management decision-support tool) and grouped them into 4 PLF technology clusters according to the level of association with each other and the area of dairy farm management in which they are used. The PLF technology clusters were reproductive management technologies, grass management technologies, milking management technologies, and calf management technologies. Additionally, we classified farms into 3 categories of intensity of technology adoption based on the number of PLF technologies they have adopted (nonadoption, low intensity of adoption, and high intensity of adoption). Second, we determined the factors associated with the intensity of technology adoption and with the adoption of the PLF technology clusters. A multinomial logistic regression model and 4 logistic regressions were used to determine the factors associated with intensity of adoption (low and high intensity of adoption compared with nonadoption) and with the adoption of the 4 PLF technology clusters, respectively. Adoption levels varied depending on PLF technology, with the most adopted PLF technologies being those related to the milking process (e.g., automatic parlor feeders and milk meters). The results of the multinomial logistic regression suggest that herd size, proportion of hired labor, agricultural education, and discussion group membership were positively associated with a high intensity of adoption, whereas age of farmer and number of household members were negatively associated with high intensity of adoption. However, when analyzing PLF technology clusters, the magnitude and direction of the influence of the factors in technology adoption varied depending on the PLF technology cluster being investigated. By identifying the PLF technologies in which pasture-based dairy farmers are investing more and by detecting potential drivers and barriers for the adoption of PLF technologies, the current study could allow PLF technology companies, practitioners, and researchers to develop and target strategies that improve future adoption of PLF technologies in pasture-based dairy settings.

**Key words:** precision livestock farming, precision technologies, technology adoption, pasture-based dairy farms

## INTRODUCTION

Precision livestock farming (**PLF**)—the use of information and communication technologies and decision-support tools to monitor animals' behavior, welfare, and production (Eastwood et al., 2012; Jelinski et al., 2020)—has been widely identified as an important approach to improve the economic, social,

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and environmental sustainability of dairy production systems (Lovarelli et al., 2020). This arises from the expectation that PLF technologies will increase farm efficiency, reduce costs, improve product quality, improve animal health and welfare, and reduce the environmental impacts of dairy farms (Bewley, 2017). Examples of PLF technologies used in dairy farms include activity sensors (leg tag or neck collars), automation technologies (e.g., automatic milking systems), and decision-support tools for reproductive and pasture management. In spite of the potential benefits of PLF technologies and a presumed working assumption that PLF adoption is desirable, there are still doubts about the actual value that PLF technologies deliver to dairy farmers (Steeneveld et al., 2015). Estimating adoption levels (the number or percentage of farms that use a PLF technology) and understanding adoption decision-making constitutes the first step to evaluate the impacts of PLF technologies on all aspects of dairy farms and to explore the limited adoption levels in some contexts. In general, profit-maximizing farmers will adopt new technologies if they perceive adoption will generate a positive net economic benefit, either by reducing the costs of producing a given level of output, increasing outputs for a given level of input, or both (Chavas and Nauges, 2020). In addition to economic factors, the process of technology adoption has been associated with relative resource scarcity such as labor, access to information by farmers, and local agro-climatic conditions (Chavas and Nauges, 2020). Previous research has found that precision agriculture technology adoption is related to many individual factors such as farm size, total income, land tenure, farmer's age and education, familiarity with computers, access to information (e.g., through extension services), and location (Pierpaoli et al., 2013). Additionally, the decision behind investing in precision dairy farming technologies is influenced by several subjective aspects (Stone, 2020).

Previous studies have investigated the adoption levels of PLF technologies in pasture-based dairy systems (Jago et al., 2011; Edwards et al., 2015; Gargiulo et al., 2018; Dela Rue et al., 2020; Yang et al., 2021) and indoor dairy systems (Borchers and Bewley, 2015; Jelinski et al., 2020), finding varying adoption levels. However, studies on pasture-based dairy systems are mostly based on voluntary online surveys, which suggest a selection bias toward dairy farmers who already use computers and the internet (Gargiulo et al., 2018), or surveyed a selected group (larger farms, rotary dairies, and using electronic identification tags) of dairy farmers (Jago et al., 2011), or were focused on the use of in-parlor technologies (Edwards et al., 2015; Dela Rue et al., 2020; Yang et al., 2021).

Few studies have investigated the factors associated with PLF technology adoption in pasture-based dairy systems (Gargiulo et al., 2018; Dela Rue et al., 2020; Yang et al., 2021). Gargiulo et al. (2018) investigated only the relationship of herd size on PLF technology adoption. Dela Rue et al. (2020) focused on the factors associated with PLF technologies installed at or near the dairy, and Yang et al. (2021) grouped PLF technologies into labor-saving (or automation) and data-capture technologies. There is limited published evidence on the adoption levels of PLF technologies, other than in-parlor technologies, and on the factors affecting adoption of PLF technologies used in different areas of dairy farm management, especially grass management technologies, despite their potential impacts on the efficiency and profitability of pasture-based dairy systems (Hanrahan et al., 2018). Therefore, the aim of this study was to establish adoption levels of 9 PLF technologies in Irish pasture-based dairy farms and to determine the factors associated with PLF technology adoption in these settings. The analysis was conducted for 3 categories of intensity of technology adoption: nonadoption, low intensity of adoption, and high intensity of adoption, and for 4 PLF technology clusters: reproductive management technologies, grass management technologies, milking management technologies, and calf management technologies. We hypothesized that adoption levels of PLF technologies are lower in pasture-based dairy systems than in indoor dairy systems, and that not all factors affect the intensity of technology adoption and the adoption of PLF technology clusters to the same extent.

## MATERIALS AND METHODS

Ethical approval was not needed for this study because no animal procedures were performed/only existing data were used.

### *Farm-Level Data*

This analysis was based on socioeconomic farm-level data collected from the 2018 National Farm Survey (**NFS**). The NFS was established in 1972 and has been conducted annually since then, in Ireland, by Teagasc, as part of the Farm Accountancy Data Network of the European Union. A statistically representative sample of approximately 900 farms is selected randomly each year in conjunction with the Central Statistics Office (**CSO**; Dillon et al., 2018). The survey data are collected through a series of face-to-face interviews throughout the year by a professional data collection team. Farms are categorized into one of 6 farming systems based on dominant farm enterprise: dairy, cattle rearing, cattle other, sheep, tillage, and mixed livestock (Dillon et al., 2018). Each surveyed farm is assigned a weighting factor or population weight that represents how many farms of Ireland are represented by the sampled farm. The sampled farm is assigned this weight based on the estimated farm population and the representation of the farm within each system and size category. This estimation is done by the CSO based on the CSO Census of Agriculture and the CSO Farm Structures Survey. A more detailed explanation of sample size and population weights is available in the 2018 NFS report (Dillon et al., 2018). A total of 311 specialized dairy farms were surveyed in the 2018 NFS, which represent a weighted population of 16,146 dairy farms in Ireland according to the CSO.

The 2018 NFS included an additional survey that asked dairy farmers about their use of 9 PLF technologies. A group of experts on the field of PLF technologies chose these technologies because they are the most commonly promoted and used PLF technologies in Ireland. They included not only in-parlor technologies but also grassland management technologies (e.g., rising plate meters) that are particularly important in pasture-based dairy settings due to their potential impact on pasture utilization and profitability (Hanrahan et al., 2018). The PLF technologies included in the survey were individual cow activity sensors, rising plate meters (including manual or Bluetooth-enabled rising plate meters), automatic washers (including automatic cluster washers, automatic milking machine washers, or automatic plant washers), automatic cluster removers, automatic calf feeders, automatic parlor feeders, automatic drafting gates, milk meters, and the use of PastureBase Ireland (**PBI**). PastureBase Ireland is a web-based grassland management decision-support tool that aims to help farmers with grassland management decisions, allowing them to grow and utilize grass in a more efficient manner (Hanrahan et al., 2017). The 2018 additional survey was completed by 274 dairy farmers.

With the original technologies included in the NFS, we created 4 PLF technology clusters (Table 1) by grouping PLF technologies based on their level of associations with each other and the area of dairy farm management in which they are used. The PLF technology clusters were reproductive management technologies (grouping adopters of individual cow activity sensors, automatic drafting gates, or both), grass management technologies (grouping adopters of rising plate meters, PBI, or both), milking management technologies (grouping adopters of automatic washers, automatic parlor feeders, automatic cluster removers, milk meters, or all) and calf management technologies (encompassing only automatic calf feeders).

Adoption data of each PLF technology were extracted from the 2018 additional survey together with farm and farmer demographic variables from the 2018 NFS. Both data sets were merged by farm codes to create a farm-level data set (n = 274) that included each of the 9 PLF technologies, the 4 PLF technology clusters, and the factors (farm and farmer characteristics that may affect technology adoption) included in the analysis: herd size (average number of cows), farm family income (**FFI**) per hectare, proportion of hired labor, farmer's age, number of household members, farmer's agricultural education, region (geographical location), and discussion group membership (Table 1). Each farm was analyzed considering their weighting factor; therefore, the total weighted population of our data set was 14,191 dairy farms based on the 274 farms that had completed the additional survey.

Finally, an "intensity of technology adoption" variable was created by classifying farms according to the number of PLF technologies they adopted: (1) nonadoption, (2) low intensity of adoption, and (3) high intensity of adoption. "Nonadoption" refers to farms adopting none of the 9 PLF technologies, "low intensity of adoption" included farms that had adopted 1 or 2 of the 9 PLF technologies, and "high intensity of adoption" included farms that had adopted 3 or more of the 9 technologies (Table 1). The classification was established by first separating the intensity of technology adoption variable in 5 categories with 2 PLF technologies adopted per category. The categories were "0" for farms that had not adopted any PLF technology, "1" for farms that had adopted 1 or 2 PLF technologies, "2" for farms that had adopted 3 or 4 PLF technologies, "3" for farms that had adopted 5 or 6 PLF technologies, and "4" for farms that had adopted >6 technologies. We conducted a multinomial logistic regression on factors influencing these 5 categories of intensity of technology adoption and found that there was no significant differences after category 3 (adoption of 3 or 4 PLF technologies); therefore, farms that had adopted 3 or more PLF technologies (categories 2, 3, and 4) were merged. Second, we conducted a sensitivity analysis of the results by testing different cuts between the 3 categories of intensity of technology adoption (e.g., establishing category 1 for farms who had adopted 1 to 3 PLF technologies

**Table 1.** Description of variables included in the regression models of adoption of precision livestock farming (PLF) technologies

| Variable | Description |
|---|---|
| PLF technologies | |
| Individual cow activity sensors | = 1 if the farmer adopted individual cow activity sensors; 0 otherwise |
| Rising plate meters | = 1 if the farmer adopted manual or Bluetooth-enabled rising plate meters; 0 otherwise |
| Automatic washers | = 1 if the farmer adopted automatic clusters washers, automatic milking machine washers, or automatic plant washers; 0 otherwise |
| Automatic cluster removers | = 1 if the farmer adopted automatic cluster removers; 0 otherwise |
| Automatic calf feeders | = 1 if the farmer adopted automatic calf feeders; 0 otherwise |
| Automatic parlor feeders | = 1 if the farmer adopted automatic parlor feeders; 0 otherwise |
| Automatic drafting gates | = 1 if the farmer adopted automatic drafting gates; 0 otherwise |
| Milk meters | = 1 if the farmer adopted milk meters; 0 otherwise |
| Pasture Base Ireland (PBI) | = 1 if the farmer adopted PBI; 0 otherwise |
| PLF technology clusters | |
| Reproductive management | = 1 if the farmer adopted activity sensors or automatic drafting gates; 0 otherwise |
| Grass management | = 1 if the farmer adopted rising plate meters or PBI; 0 otherwise |
| Milking management | = 1 if the farmer adopted automatic cluster removers, automatic milk washers, automatic parlor feeders, or milk meters; 0 otherwise |
| Calf management | = 1 if the farmer adopted automatic calf feeders; 0 otherwise |
| Intensity of PLF technology adoption | |
| Intensity of technology adoption (3 categories) | = 0 if the farm has not adopted any technologies (= nonadoption);<br>= 1 if the farm adopted 1 or 2 technologies (= low intensity of adoption);<br>= 2 if the farm adopted ≥3 technologies (= high intensity of adoption) |
| Factors | |
| Herd size | Average number of dairy cows |
| Farm family income (FFI) | Euros (€) per hectare of farm |
| Hired labor | Paid labor units as a proportion of total labor units |
| Age | Age of the farmer |
| Household | Number of household members |
| Agricultural education (3 categories) | = 0 if the farmer has no agricultural education;<br>= 1 if the farmer has high agricultural education (completed a full-time third-level agricourse, farm apprenticeship scheme, or a certificate in farming);<br>= 2 if the farmer has medium agricultural education (completed 1 yr of college agricultural education, a course of >60 h, a course of <60 h, or others) |
| Region (3 categories) | = 1 if farm is in the northwest region (counties Louth, Leitrim, Sligo, Cavan, Donegal, Monaghan, Galway, Mayo, or Roscommon);<br>= 2 if farm is in the mideast region (counties Dublin, Kildare, Meath, Wicklow, Laois, Longford, Offaly, or Westmeath);<br>= 3 if farm is in the southwest region (counties Clare, Limerick, Tipperary, Carlow, Kilkenny, Wexford, Waterford, Cork, or Kerry) |
| Discussion group membership | = 1 if the farmer is a member of a discussion group; 2 otherwise |

instead of 1 or 2). The results did not significantly change; therefore, we kept the original 3 categories of intensity of technology adoption.

### *Statistical Methods*

All statistical analyses were performed using R statistical software (version 4.0.2; R Core Team, 2020). Adoption percentages of PLF technologies were retrieved from the 2018 NFS to establish the adoption levels of each PLF technology. Pairwise Fisher's exact tests (fisher.test function in R) were conducted to identify associations between PLF technologies and to group the PLF technology clusters (Appendix Table A1).

A multinomial logistic regression model was applied using the *multinom* function in R (*nnet* package) to determine the factors associated with intensity of technology adoption (nonadoption, low intensity of adoption, and high intensity of adoption). Equation [1] shows the model specification:

$$\log\left[\frac{P(Y_i = k)}{P(Y_i = 0)}\right] = \beta_{0k} + \beta_{1k} herd_i + \beta_{2k} herd_i^2 + \beta_{3k} FFI_j + \beta_{4k} FFI_j^2 + \beta_{5k} labor_l + \beta_{6k} age_m + \beta_{7k} age_m^2 + \beta_{8k} house_n + \beta_{9k} educ_o + \beta_{10k} region_p + \beta_{11k} disc_q + e_{ijklmnopq};\ k = 1, 2, \quad [1]$$

where $Y_i$ is the 3-category outcome variable "intensity of technology adoption." Since there are 3 categories and the reference category is set to be nonadoption ($Y_i = 0$), the model provides 2 sets of regression results (for low and high intensity of adoption). The explanatory variables $X_i$ are described in Table 2, and $e_{ijklmnopq}$ is the error term. We also included $herd_i^2$, $FFI_j^2$, and $age_m^2$ in the model to test for a quadratic effect of these vari-

**Table 2.** Descriptive statistics of the explanatory variables included in the regression models for intensity of technology adoption and precision livestock farming (PLF) technology clusters on Irish dairy farms

| Variable | Model specification[1] ($X_i$) | Sampled farms | | | | Weighted population | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Minimum | Maximum | Mean | SD | Minimum | Maximum | Mean | SD |
| Weighting factor | | 28.07 | 102.94 | 51.72 | 18.01 | 28.07 | 102.94 | | |
| Continuous explanatory variables | | | | | | | | | |
| Herd size (no. of cows) | $herd_i$ | 10.00 | 318.42 | 91.14 | 54.63 | 10.00 | 318.42 | 78.67 | 47.67 |
| Farm family income (€/ha) | $FFI_j$ | −273.5 | 3,375.4 | 1,052.4 | 568.24 | −273.5 | 3,375.4 | 1,063.3 | 593.72 |
| Proportion of hired labor | $labor_l$ | 0.00 | 0.75 | 0.14 | 0.19 | 0.00 | 0.75 | 0.11 | 0.17 |
| Age (yr) | $age_m$ | 23.00 | 76.00 | 52.96 | 10.29 | 23.00 | 76.00 | 52.92 | 9.91 |
| Household members (no.) | $house_n$ | 1.00 | 8.00 | 3.43 | 1.48 | 1.00 | 8.00 | 3.36 | 1.45 |
| Categorical explanatory variables | | | Relative frequency | | | | Relative frequency | | |
| Agriculture (ag) education (3 categories) | $educ_o$ | | | | | | | | |
| No ag education (category 0) | | | 0.18 | | | | 0.21 | | |
| High ag education (category 1) | | | 0.32 | | | | 0.31 | | |
| Medium ag education (category 2) | | | 0.50 | | | | 0.49 | | |
| Region (3 categories) | $region_p$ | | | | | | | | |
| Northwest (category 1) | | | 0.16 | | | | 0.18 | | |
| Mideast (category 2) | | | 0.18 | | | | 0.16 | | |
| Southwest (category 3) | | | 0.66 | | | | 0.66 | | |
| Discussion group membership | $disc_q$ | | | | | | | | |
| Yes | | | 0.47 | | | | 0.42 | | |
| No | | | 0.53 | | | | 0.58 | | |

[1]Symbol of the explanatory variables in the regression model specifications.

ables. The regression coefficients $\beta$ are expressed as log odds. The weighting factor for each farm was included using the argument "weights" in the model to ensure representative results.

Four binomial logistic regression models were applied using the *glm* function in R to determine the factors associated with adoption of each PLF technology cluster. Equation [2] shows the model specification:

$$Log\left[\frac{P(Y_i=1)}{P(Y_i=0)}\right] = \beta_0 + \beta_1 herd_i + \beta_2 herd_i^2 + \beta_3 FFI_j + \beta_4 FFI_j^2 + \beta_5 labor_k + \beta_6 age_l + \beta_7 age_l^2 + \beta_8 house_m + \beta_9 educ_n + \beta_{10} region_o + \beta_{11} disc_p + e_{ijklmnop}, \quad [2]$$

The outcome binary variables ($Y_i$) in each situation were the adoption of a PLF technology cluster ($Y_i =$ 1 if adopted, 0 otherwise). The explanatory variables were the same as for the multinomial logistic regression model (Table 2). The weights argument was included in the regressions to ensure representative results.

The results of the multinomial logistic regression and the binomial logistic regressions are presented as odds ratios with their standard errors. Although the coefficients only allow us to identify the sign of the effect of the explanatory variables on the outcome variable, odds ratios allow us to interpret both the sign and magnitude of the effect. The odds ratios were calculated by exponentiation of the multinomial and binomial logistic regressions coefficients. Statistical significance was determined if $P < 0.05$. Multicollinearity (condition in which one explanatory variables is highly correlated with one or more of the other explanatory variables in the regression) was tested by estimating the variance inflation factor (**VIF**) using the *vif* function of the *car* package in R, and considered of concern if VIF >5.

## RESULTS

### *Adoption Levels of PLF Technologies*

The percentage of adoption of PLF technologies in Irish dairy farms is presented in Table 3. The results showed that the most adopted PLF technologies by Irish dairy farmers were automatic parlor feeders, followed by milk meters, automatic washers, automatic cluster removers, and PBI. Conversely, rising plate meters were the least adopted PLF technology by Irish dairy farmers, followed by automatic drafting gates, automatic calf feeders, and individual cow activity sensors. About 30% of Irish dairy farmers declared they did not have any PLF technologies.

### Factors Associated with Intensity of Technology Adoption

The results of the multinomial logistic regression model are reported as odds ratios in Table 4. The odds ratio of each variable was estimated comparing low intensity of adoption and high intensity of adoption with nonadoption (our baseline). Dairy farms with larger herd sizes were associated with a higher likelihood of PLF technology adoption (low intensity of adoption and high intensity of adoption; $P < 0.001$) compared with nonadoption. However, the effect of herd size in technology adoption was not linear, which means that when herd size increased, farms were more likely to adopt PLF technologies until herd size reached a certain point or optimal level. After this point, the adoption of PLF technologies remained constant (forms a plateau) or began to fall. Dairy farms with a higher proportion of hired labor, as opposed to unpaid family labor, and discussion group members were positively associated with high intensity of adoption ($P < 0.001$).

Conversely, older dairy farmers were associated with a lower likelihood of PLF technology adoption (low intensity of adoption and high intensity of adoption; $P < 0.001$), but as with herd size, the age effect was not linear. Dairy farmers with more household members were associated with a lower likelihood of PLF technology adoption (low intensity of adoption and high intensity of adoption; $P < 0.001$). The model showed that dairy farmers with a high level of agricultural education were positively associated with high intensity of adoption ($P < 0.001$) compared with farmers without agricultural education. Finally, model results also showed that dairy farmers of the mideast region of Ireland were negatively associated with high intensity of adoption ($P < 0.001$) compared with farmers in the northwest region, and dairy farms in the southwest were negatively associated with low intensity of adoption ($P < 0.001$) but positively associated with high intensity of adoption ($P < 0.001$) compared with dairy farmers in the northwest region. Multicollinearity was tested and found to be of no concern (VIF <5).

### Factors Associated with Adoption of PLF Technology Clusters

The results of 4 binomial logistic regression models, one per PLF technology cluster, are presented as odds ratios in Table 5. The results suggest that dairy farms with larger herd sizes were more likely to adopt all PLF technology clusters ($P < 0.001$) but at a decreasing rate (nonlinear effect). The age factor also had a significant association with the likelihood of adopting all PLF technology clusters but the direction of the effect differed among clusters. Younger dairy farmers were more likely to adopt reproductive ($P < 0.001$) and grass management technologies ($P < 0.001$), whereas older dairy farmers were more likely to adopt milking ($P < 0.001$) and calf management technologies ($P < 0.001$). The proportion of hired labor was positively associated with the likelihood of adopting grass ($P < 0.001$), milking ($P = 0.0026$), and calf management technologies ($P = 0.0203$), and negatively associated with the likelihood of adopting reproductive management technologies ($P = 0.0163$). The results of the regressions also showed that number of household members was positively associated with the likelihood of adopting reproductive management technologies ($P < 0.001$) but negatively associated with the odds of adopting milking ($P < 0.001$) and calf management technologies ($P < 0.001$); there was no association with the adoption of grass management technologies. High agricultural education was positively associated with the likelihood of adopting reproductive ($P < 0.001$) and calf management technologies ($P = 0.0378$), whereas medium agricultural education was positively associated with reproductive ($P = 0.0014$) and grass management technologies ($P < 0.001$). There was no association of any type of agricultural education with the adoption of milking management technologies. There were significant differences in the geographic location of the adopters of PLF technology clusters. Dairy farms located in the mideast and southwest regions of Ireland adopted more grass, milking, and calf management technologies compared with those of the northwest region, but they adopted fewer reproductive management technologies. Discussion group membership was found to have a positive association with the likelihood of adopting reproductive ($P < 0.001$) and grass ($P < 0.001$) management technologies and a negative association with the odds of adopting milking ($P = 0.0118$) and calf ($P < 0.001$) management technologies. Multicollinearity was tested and found to be of no concern (VIF <5).

## DISCUSSION

### Adoption Levels of PLF Technologies in Pasture-Based Dairy Systems

Reporting on adoption levels of PLF technologies is important for understanding the ongoing technological transformation of the dairy sector. This is one of a few articles focused on pasture-based dairy systems, and the first in Ireland. We provide much-needed detail regarding this technological transformation that allows us to better understand the acceptability of PLF technologies by dairy farmers and the area of dairy farm management in which farmers are investing more in

**Table 3.** Percentage of adoption (%) of precision livestock farming (PLF) technologies in Irish dairy farms

| PLF technology | Sampled farms (n) | Adoption[1] (%) | Weighted population | Adoption[2] (%) |
|---|---|---|---|---|
| Rising plate meters | 21 | 7.7 | 890 | 6.3 |
| PastureBase Ireland | 76 | 27.7 | 3,426 | 24.1 |
| Individual cow activity sensors | 23 | 8.4 | 946 | 6.7 |
| Automatic drafting gates | 30 | 10.9 | 1,085 | 7.6 |
| Automatic washers | 83 | 30.3 | 3,772 | 26.6 |
| Automatic clusters removers | 86 | 31.4 | 3,483 | 24.5 |
| Milk meters | 89 | 32.5 | 4,073 | 28.7 |
| Automatic parlor feeders | 159 | 58.0 | 7,424 | 52.3 |
| Automatic calf feeders | 28 | 10.2 | 1,199 | 8.3 |
| No technologies | 68 | 24.8 | 4,272 | 30 |
| Total | 274 | | 14,191 | |

[1]Percentage of adoption of the sampled farms.

[2]Percentage of adoption of the weighted population

**Table 4.** Regressions odds ratios (SE in parentheses) and *P*-values for factors associated with the intensity of technology adoption

| | Low intensity of adoption[1] | | High intensity of adoption[2] | |
|---|---|---|---|---|
| Variable | Odds ratio | *P*-value | Odds ratio | *P*-value |
| Herd size (no. of cows) | 1.05 | <0.001 | 1.09 | <0.001 |
| | (7.41 E-8) | | (1.64 E-7) | |
| Herd size squared | 0.99 | <0.001 | 0.99 | <0.001 |
| | (4.48 E-6) | | (4.45 E-6) | |
| FFI (€/ha) | 1.002 | <0.001 | <1.001[3] | <0.001 |
| | (1.18 E-6) | | (1.88 E-6) | |
| FFI squared | 0.99 | <0.001 | 1.00 | 0.4849 |
| | (1.61 E-8) | | (1.75 E-8) | |
| Proportion of hired labor | 8.31 | <0.001 | 18.09 | <0.001 |
| | (9.32 E-11) | | (1.70 E-10) | |
| Age (yr) | 0.90 | <0.001 | 0.85 | <0.001 |
| | (1.66 E-7) | | (2.07 E-7) | |
| Age squared | 1.001 | <0.001 | 1.002 | <0.001 |
| | (9.94 E-6) | | (1.32 E-5) | |
| Household members (no.) | 0.87 | <0.001 | 0.90 | <0.001 |
| | (7.68 E-9) | | (8.73 E-9) | |
| High agricultural (ag) education[4] | 0.90 | <0.001 | 2.47 | <0.001 |
| | (4.10 E-10) | | (3.60 E-10) | |
| Medium ag education[4] | 1.02 | <0.001 | 1.67 | <0.001 |
| | (1.23 E-9) | | (2.10 E-9) | |
| Mideast region[5] | 1.03 | <0.001 | 0.73 | <0.001 |
| | (4.09 E-10) | | (7.90 E-11) | |
| Southwest region[5] | 0.86 | <0.001 | 1.06 | <0.001 |
| | (1.38 E-9) | | (2.61 E-9) | |
| Discussion group membership[6] | 1.27 | <0.001 | 3.05 | <0.001 |
| | (6.50 E-10) | | (1.37 E-9) | |
| Constant | 1.09 | <0.001 | 0.04 | <0.001 |
| | (2.80 E-9) | | (3.20 E-9) | |
| Residual deviance | 23,530.87 | | 23,530.87 | |
| Akaike information criterion | 23,586.87 | | 23,586.87 | |

[1]Dairy farms that have adopted 1 or 2 precision livestock farming (PLF) technologies, compared with farms without PLF technologies (nonadoption).

[2]Dairy farms that have adopted 3 or more PLF technologies compared with farms without PLF technologies (nonadoption).

[3]Odds ratio of 1.000086.

[4]No agricultural education as reference category.

[5]Northwest region as reference category.

[6]No discussion group membership as reference category.

PLF technologies in pasture-based settings. Importantly, this could be used as a baseline for future research on PLF technology adoption trends.

The results showed that Irish dairy farmers most commonly adopted PLF technologies around the milking process (automatic parlor feeders, milk meters, automatic washers, and automatic cluster removers). Similar results were reported in other countries with pasture-based dairy systems (Edwards et al., 2015; Gargiulo et al., 2018; Dela Rue et al., 2020), mixed dairy systems (Groher et al., 2020), and indoor systems (Borchers and Bewley, 2015), albeit with differences in technology adoption levels. For example, automatic cluster removers are the most commonly adopted technology by New Zealand (Edwards et al., 2015) and Australian dairy farmers (Gargiulo et al., 2018). Approximately 39% of New Zealand dairy farms (Dela Rue et al., 2020) and 66% of Australian dairy farms (Gargiulo et al., 2018) adopted automatic cluster removers compared with 25% of Irish dairy farms. This difference might be because New Zealand and Australian dairy farms have relatively larger herd sizes than Irish dairy farms (Deming et al., 2018). Approximately 40% of New Zealand dairy farmers (Dela Rue et al., 2020) and 39% of Australian dairy farmers (Gargiulo et al., 2018) adopted automatic parlor feeders, whereas 52% of Irish dairy farmers adopted this technology. Milk meters were the most frequently adopted technology by Swiss dairy farmers, with 45% of adoption (Groher et al., 2020), whereas 29% of Irish dairy farmers and 8% of New Zealand dairy farmers have adopted milk meters. Furthermore, more than half of dairy farmers in the United States declared that they adopted technologies to monitor daily milk yields (Borchers and Bewley, 2015).

The higher adoption levels of milking management technologies might be because the milking process is physically demanding and time consuming, accounting for the majority of labor required on pasture-based dairy systems (Deming et al., 2018). Therefore, the benefits of using this type of precision technology are greater (Edwards et al., 2015) and quickly perceived by dairy farmers (Groher et al., 2020) in an environment of scarce and costly labor. Additionally, most of this group of technologies are automation technologies, which are highly valued by dairy farmers (Dela Rue et al., 2020).

Adoption levels of grass measuring technologies are still low on pasture-based dairy systems. About 15% of Australian dairy farmers adopted grass measuring technologies (Gargiulo et al., 2018), whereas only 6% of Irish dairy farmers adopted rising plate meters. Given that pasture utilization is the greatest driver of profitability and efficiency at the farm level on pasture-based dairy farms (Hanrahan et al., 2018), there is potential to increase the uptake of grass measuring tools such as rising plate meters. Grass management technologies, on the other hand, showed higher adoption levels. A quarter of Irish dairy farmers have adopted PBI, a web-based grassland management application created in 2013 that provides decision support for farmers while also generating farm grassland national data for research purposes (Hanrahan et al., 2017). It has been reported that farms that adopted PBI have increased pasture growth (O'Leary and O'Donovan, 2019), which is likely to translate into an increase in pasture utilization with higher profitability at the farm level (Hanrahan et al., 2018). The economic benefits that farmers perceived when using PBI might explain the high adoption rates.

Adoption of individual cow activity sensors is also low in pasture-based dairy systems, especially compared with indoor milking systems. About 8% of Australian dairy farms (Gargiulo et al., 2018), 3% of New Zealand dairy farms (Dela Rue et al., 2020), and 7% of Irish dairy farms adopted this PLF technology. About 2.5% of Swiss dairy farmers use individual cow activity sensors (Groher et al., 2020), and around 40% of dairy farmers in the United States declared having adopted this technology to monitor cow activity (Borchers and Bewley, 2015). This might be because access to activity sensors, such as heat detection devices, is relatively new on pasture-based dairy systems and there is a smaller market size compared with indoor dairy systems (Shalloo et al., 2021). Additionally, there are still concerns on the accuracy of the data delivered to dairy farmers (O'Leary et al., 2020). Moreover, data-capture technologies such as sensors are more difficult for dairy farmers to use because they depend more on knowledgeable operators to interpret the data (Dela Rue et al., 2020), therefore limiting their adoption.

The analysis of the associations between PLF technologies (Appendix Table A1) showed that certain types of PLF technologies tend to be adopted together. This suggests that future research on PLF technologies should study not only the individual but also the cumulative benefits of PLF technologies to promote them as PLF technology clusters to farmers, which could lead to higher adoption levels.

### *Factors Associated with the Intensity of Technology Adoption*

As reported by other studies of precision technology adoption in pasture-based dairy systems (Gargiulo et al., 2018) and indoor dairy systems (Jelinski et al., 2020), we found that herd size was positively associated

**Table 5.** Regressions odds ratios (SE in parentheses) and *P*-values for factors associated with the adoption of precision livestock farming (PLF) technology clusters

| | PLF technology cluster[1] | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Reproductive management | | Grass management | | Milking management | | Calf management | |
| Variable | Odds ratio | *P*-value | Odds ratio | *P*-value | Odds ratio | *P*-value | Odds ratio | *P*-value |
| Herd size (no. of cows) | 1.05 (2.43 E-3) | <0.001 | 1.03 (1.67 E-3) | <0.001 | 1.05 (1.85 E-3) | <0.001 | 1.05 (2.47 E-3) | <0.001 |
| Herd size squared | 0.99 (7.78 E-6) | <0.001 | 0.99 (5.86 E-6) | <0.001 | 0.99 (8.51 E-6) | <0.001 | 0.99 (8.01 E-6) | <0.001 |
| FFI (€/ha) | 0.99 (1.65 E-4) | <0.001 | 0.99 (1.42 E-4) | <0.001 | 1.001 (1.07 E-4) | <0.001 | 1.001 (2.30 E-4) | <0.001 |
| FFI squared | <1.001[2] (5.59 E-8) | <0.001 | <1.001[3] (5.35 E-8) | <0.001 | 0.99 (3.90 E-8) | <0.001 | 0.99 (8.42 E-8) | <0.001 |
| Proportion of hired labor | 0.63 (1.95 E-1) | 0.0163 | 4.94 (1.58 E-1) | <0.001 | 1.83 (2.00 E-1) | 0.0026 | 1.61 (2.06 E-1) | 0.0203 |
| Age (yr) | 0.90 (2.21 E-2) | <0.001 | 0.81 (1.70 E-2) | <0.001 | 1.07 (1.70 E-2) | <0.001 | 1.18 (3.20 E-2) | <0.001 |
| Age squared | 1.001 (2.20 E-4) | <0.001 | 1.002 (1.66 E-4) | <0.001 | 0.99 (1.64 E-4) | 0.0398 | 0.99 (2.89 E-4) | 0.0012 |
| Household (no.) | 1.13 (2.40 E-2) | <0.001 | 1.03 (1.71 E-2) | 0.0699 | 0.92 (1.55 E-2) | <0.001 | 0.84 (2.85 E-2) | <0.001 |
| High agricultural (ag) education[4] | 3.69 (1.24 E-1) | <0.001 | 1.15 (7.89 E-2) | 0.0718 | 0.99 (6.43 E-2) | 0.9011 | 1.25 (1.07 E-1) | 0.0378 |
| Medium ag education[4] | 1.44 (1.15 E-1) | 0.0014 | 1.22 (7.02 E-2) | 0.0047 | 1.01 (5.68 E-2) | 0.8040 | 0.30 (9.81 E-2) | <0.001 |
| Mideast region[5] | 0.68 (1.01 E-1) | 0.0001 | 1.20 (8.97 E-2) | 0.0418 | 1.65 (7.72 E-2) | <0.001 | 1.48 (1.94 E-1) | 0.0426 |
| Southwest region[5] | 0.23 (9.20 E-2) | <0.001 | 1.87 (7.31 E-2) | <0.001 | 1.21 (5.64 E-2) | 0.0005 | 6.88 (1.76 E-1) | <0.001 |
| Discussion group membership[6] | 2.62 (7.38 E-2) | <0.001 | 7.22 (5.21 E-2) | <0.001 | 0.89 (4.69 E-2) | 0.0118 | 0.65 (7.56 E-2) | <0.001 |
| Constant | 0.04 (5.97 E-1) | <0.001 | 2.43 (4.51 E-1) | 0.0494 | 0.01 (4.50 E-1) | <0.001 | 8.90 E-7 (9.49 E-1) | <0.001 |
| Log-likelihood | −3,188.93 | | −5,944.91 | | −7,182.01 | | −2,987.63 | |
| AIC | 6,405.86 | | 11,917.83 | | 14,392.03 | | 6,003.26 | |

[1]Adopters of a PLF technology cluster compared with nonadopters.
[2]Odds ratio of 1.0000006.
[3]Odds ratio of 1.0000005.
[4]No agricultural education as reference category.
[5]Northwest region as reference category.
[6]No discussion group membership as reference category.

with the adoption of PLF technologies. This association was greater for farmers that adopted a higher number of technologies (high intensity of adoption).

Proportion of hired labor was shown to be an important factor associated with intensity of PLF technology adoption. Jelinski et al. (2020) reported similar results in Canadian dairy farms, showing that dairy farms with a higher number of operators (≥2) were also more likely to adopt precision technologies compared with single operator farms. This may be explained because labor has been reported as the second highest cost on pasture-based dairy systems (Deming et al., 2018). Additionally, improving labor efficiency and reducing hired labor are one of the most important drivers for technology adoption, with farmers investing more in automation (or labor-saving technologies) than others (Gargiulo et al., 2018; Dela Rue et al., 2020; Yang et al., 2021).

Younger dairy farmers are more likely to adopt a higher number of PLF technologies, but at a decreasing rate (nonlinear effect). Therefore, there is a need to promote PLF technologies at the appropriate part of the life cycle of a farmer. Similar findings were found in New Zealand (Yang et al., 2021) and Canadian (Jelinski et al., 2020) dairy farms. This might be because younger generations are more accepting of new technologies in general (Pierpaoli et al., 2013), they find it more useful than older farmers do (Rose et al., 2016), and they might be better able to utilize the technology.

The significant and negative association between the number of household members and high intensity of technology adoption suggests that dairy farmers with more household members are less likely to adopt these technologies due to the greater availability of family members to work on the farm, which means they depend less on hired labor.

As reported in other studies (Pierpaoli et al., 2013), we found that dairy farmers with some level of agricultural education were more likely to adopt PLF technologies compared with dairy farmers without agricultural education, and that dairy farmers with a high level of agricultural education were more likely to adopt a greater number of PLF technologies (high intensity of adoption). This might be because high levels of agricultural education within the dairy farming community may result in farmers more knowledgeable and skilled in the use of PLF technologies. This group may also perceive greater benefits from adopting a large number of technologies, a concept called "relative advantage" by Stone (2020).

Geographic regional differences in PLF technology adoption were also reported in New Zealand (Yang et al., 2021) and Canadian (Jelinski et al., 2020) dairy farms. The southwest region of Ireland has a greater proportion of dairy production with free-draining soils, and it is therefore an advantaged region in terms of productivity and profitability compared with the mideast and northwest regions (Shalloo et al., 2004; Läpple et al., 2013). This may explain why we found that dairy farms located in the southwest region were more likely to adopt a higher number of PLF technologies compared with dairy farms located in the northwest.

The positive and significant association between discussion group membership and high intensity of adoption is consistent with the results of other studies that assessed the effects of discussion group membership on technology adoption in Ireland (Hennessy and Heanue, 2012). The information provided by extension services (Pierpaoli et al., 2013) and the opinions and experiences shared by other farmers (a concept called "observability") through discussion groups are important drivers of precision technologies adoption (Stone, 2020) and may influence the adoption of multiple PLF technologies.

### *Factors Associated with Adoption of PLF Technology Clusters*

In addition to identifying the factors associated with intensity of technology adoption, the current study provides insights into the influence of these factors on the adoption of PLF technologies used in different areas of dairy farm management. The results showed that not all factors affected adoption of all clusters of PLF technologies, and that the magnitude and direction of the influence of the factors in technology adoption differed depending on the PLF technology cluster being investigated. For example, we found that age had both a negative association with the likelihood of adopting reproductive and grass management technologies and a positive association with the likelihood of adopting milking and calf management technologies. This might be explained because milking management technologies require significant capital investments (Yang et al., 2021), which may be more difficult for younger dairy farmers to access. Furthermore, milking and calf management technologies might be seen as more labor saving, whereas reproductive and grass management technologies could be seen as efficiency and productivity technologies. These priorities likely change with farmer age.

The negative association between the number of household members and the likelihood of adoption of milking and calf management technologies suggests greater availability of household members to work on milking tasks and calf care, and thus less need to invest in these labor-saving technologies. This is consistent with our findings on the association of hired labor with adoption of milking and calf management technologies. Another important difference within PLF technology clusters is on agricultural education. We found a strong association between high levels of agricultural education and the likelihood of adopting reproductive management technologies. This may be because this type of technology requires users to have greater knowledge to interpret data (Dela Rue et al., 2020). There are also regional differences in the adoption of PLF technology clusters. Whereas dairy farmers in the southwest region of Ireland were more likely to adopt grass, milking, and calf management technologies, they were less likely to adopt reproductive management technologies than dairy farmers in the northwest region. Finally, the negative association of discussion group membership with the likelihood of adopting milking management technologies and calf management technologies may relate to the age of discussion group members, who are, on average, younger than nonmembers (Hennessy and Heanue, 2012) and, as discussed previously, are more willing to adopt new precision technologies, such as individual cow activity sensors, rising plate meters, or PBI.

Future research should include behavioral studies on the adoption of PLF technology clusters that further increase our knowledge on the decision-making process by pasture-based dairy farmers.

## CONCLUSIONS

The current study reports the first assessment of PLF technology adoption levels on pasture-based dairy farms in Ireland, which can be used as a baseline for future research on PLF technology adoption trends. We determined several factors associated with intensity of technology adoption and with adoption of 4 PLF technology clusters in pasture-based dairy systems. Overall, herd size, proportion of hired labor, agricultural education, and discussion group membership were positively associated with the likelihood of adopting a high number of PLF technologies (high intensity of adoption), whereas age and number of household members were negatively associated with intensity of adoption. However, we found differences on the most important factors influencing the adoption of PLF technology clusters. Thus, a more nuanced understanding of the potential drivers and barriers for the adoption of PLF technologies used in specific farm management areas of pasture-based dairy systems, which we have provided in this study, would allow PLF technology companies, PLF researchers, and practitioners to develop and target strategies to improve future adoption of PLF technologies in pasture-based dairy settings.

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## Appendix

**Table A1.** Odds ratios (95% CI in parentheses) between precision livestock farming (PLF) technologies in Irish dairy farms

| | PLF[1] | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| PLF | AS | RPM | AW | ACR | ACF | APF | ADG | MM | PBI |
| AS | | | | | | | | | |
| RPM | 1.93<br>(0.33–7.51) | | | | | | | | |
| AW | 4.07**<br>(1.56–11.20) | 2.8*<br>(1.01–7.58) | | | | | | | |
| ACR | 3.84**<br>(1.47–10.55) | 3.20*<br>(1.18–9.02) | 5.95***<br>(3.27–10.98) | | | | | | |
| ACF | 3.64*<br>(1.06–11.03) | 0.91<br>(0.09–4.17) | 3.00**<br>(1.26–7.26) | 6.76***<br>(2.69–18.64) | | | | | |
| APF | 2.16<br>(0.78–6.95) | 7.62**<br>(1.77–69.02) | 3.38***<br>(1.83–6.46) | 5.34***<br>(2.79–10.79) | 3.70**<br>(1.31–12.89) | | | | |
| ADG | 17.48***<br>(6.11–52.08) | 3.78*<br>(1.09–11.60) | 9.97***<br>(3.90–28.92) | 19.68***<br>(6.46–80.66) | 5.02**<br>(1.77–13.54) | 11.99***<br>(2.91–106.25) | | | |
| MM | 3.63**<br>(1.39–9.95) | 2.45<br>(0.90–6.75) | 2.89***<br>(1.63–5.16) | 4.86***<br>(2.71–8.82) | 3.14**<br>(1.32–7.68) | 3.06***<br>(1.70–5.67) | 5.03***<br>(2.12–12.70) | | |
| PBI | 5.79***<br>(2.18–16.59) | 10.18***<br>(3.38–37.05) | 2.09*<br>(1.15–3.78) | 3.36***<br>(1.86–6.12) | 2.12<br>(0.86–5.08) | 2.81***<br>(1.51–5.39) | 4.77***<br>(2.04–11.57) | 2.65**<br>(1.47–4.78) | |

[1]AC = activity sensors; RPM = rising plate meters; AW = automatic washers; ACR = automatic cluster removers; ACF = automatic calf feeders; APF = automatic parlor feeders; ADG = automatic drafting gates; MM = milk meters; PBI = PastureBase Ireland.

***$P < 0.001$, **$P < 0.01$, *$P < 0.05$: Odds ratio is significantly different or tends to be different from 1.