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Understanding heterogeneity in technology adoption among Indonesian smallholder dairy farmers

Rida Akzar | Wendy Umberger | Alexandra Peralta

Centre for Global Food and Resources, School of Economics and Public Policy, The University of Adelaide, Adelaide, South Australia, Australia

Correspondence

Wendy Umberger, Centre for Global Food and Resources, School of Economics and Public Policy, University of Adelaide, Level 6, Nexus 10 Building, 10 Pulteney St, Adelaide, SA 5005, Australia.

Email: wendy.umberger@gmail.com

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Abstract

This study aims to understand and profile smallholder farmers' technology adoption status. We collected cross-sectional data from 600 smallholder dairy farming households in West Java, Indonesia. A Latent class cluster analysis identified two unique clusters of smallholder dairy farmers based on patterns in their adoption status of multiple dairy farming technologies. Cluster 1 (Low awareness/low adoption) had significantly lower awareness of all technologies, and among the "aware" farmers, technology adoption rates were also significantly lower compared to Cluster 2 (High awareness/high adoption). The Low awareness/low adoption cluster was older, had less formal education, managed fewer dairy cows, had less productive and less profitable dairy enterprises, lived further away from their cooperative and farmer group leader, and had fewer contacts with dairy extension staff. Farmers' responses to questions regarding reasons underpinning nonadoption decisions suggest that farmers face multilayered and heterogenous constraints to adopting dairy technologies. This insight can assist government,

Abbreviations: ANOVA, analysis of variance; BIC, Bayesian Information Criteria; BVR, bivariate residuals; FAO, Food and Agricultural Organization of the United Nations; F2F, farmer-to-farmer; GDP, Global Dairy Platform; GKSI, Indonesian Dairy Cooperatives Union; ICT, information and communication technology; IFCN, International Farm Comparison Network; LCCA, Latent class cluster analysis; OECD, Organization for Economic Cooperation and Development; SCC, somatic cell count; TPC, total plate count; TS, total solids; USD, United States Dollar.

policymakers, and development professionals in designing technology dissemination programs that meet the unique characteristics of subgroups of farmers, ultimately improving the adoption of technologies. [EconLit Citations: Q12, Q16].

KEYWORDS

adoption, Indonesia, latent class cluster analysis, multiple technologies, smallholder dairy farmers, West Java

1 | INTRODUCTION

Dairy production is a vital source of household income for many smallholder households (Duncan et al., 2013; FAO GDP & IFCN, 2018; Knips, 2005). Increasing smallholder milk production and quality remain a critical development agenda issue for achievement through introducing and encouraging the adoption of dairy technologies and improved management practices. Agricultural extension and technology dissemination programs aim to facilitate and enhance smallholder farmers' technology adoption (Anderson & Feder, 2007; Maertens et al., 2021). However, the dissemination approach in most countries has tended to follow a one-size-fits-all model, neglecting the unique characteristics of different groups of farmers (e.g., sociodemographic, assets, constraints, and adoption status) (Baloch & Thapa, 2018; Birner et al., 2009; Hammond et al., 2020); thus, resulting in low adoption of technologies by smallholders.

Tailored technology dissemination strategies that consider the distinct characteristics of farmers and address their constraints and needs have the potential to result in increased technology adoption rates (Kaliba et al., 2020; Umberger et al., 2015). However, identifying which farmers need to be targeted and determining how to tailor strategies to improve smallholder adoption is challenging because smallholder farmers are heterogeneous in their socioeconomic characteristics, production decisions, adoption status and constraints in adopting various agricultural technology options (Alexander et al., 2018; Brown et al., 2017; Feder et al., 1985; Kuivanen et al., 2016). Yet, the long-standing literature on agricultural technology adoption seems insufficient to direct the improvement of (or designing tailored) technology dissemination strategies, especially in the smallholder dairy farming context.

Most technology adoption studies focus on binary adoption decisions (adoption and nonadoption). This limited focus of past research is contrary to the fact that agricultural technology adoption is a complex and dynamic process, suggesting that farmers adopt agricultural technologies at different rates and to different extents (Brown et al., 2017; Jabbar et al., 2003; Montes de Oca Munguia et al., 2021; Weersink & Fulton, 2020). A growing body of literature considers the varied status of adoption of agricultural technologies (e.g., awareness, dis-adoption, continued adoption) to better understand farmers' uptake of agricultural technologies (e.g., Brown et al., 2017; Floyd et al., 2003; Jabbar et al., 2003; Lambrecht et al., 2014; Montes de Oca Munguia et al., 2021).

The majority of prior agricultural technology adoption research has considered the adoption of single technologies. However, smallholder farmers are often faced with multiple technology options, which can be adopted separately or as a package (Byerlee & Polanco, 1986; Dorfman, 1996; Feder et al., 1985; Rauniyar & Goode, 1992). These adoption decisions are likely to depend on the characteristics of both the farmers and the technologies, and farmers' experiences, perceptions, and expectations of the different technologies available to them. Therefore, considering smallholder farmers' adoption status for multiple technologies, rather than just a single technology, is warranted.

Moreover, most adoption studies focus on "green revolution" type technologies (e.g., improved seed varieties and fertilizers) and conservation practices in the context of farming crops (Arslan et al., 2022; Liu et al., 2018; Ruzzante et al., 2021). This attention is reasonable because the cropping sector is the primary source of staple foods globally. However, opportunities to improve technology adoption in the dairy sector also deserve attention, especially in developing countries, where there is increasing demand for protein-based foods, including milk and other dairy products (OECD/FAO, 2020), and because of its critical contribution to household income for many smallholder farming systems.

Considering the importance of improving smallholder dairy farmers' adoption of agricultural technologies through targeted technology dissemination strategies, this study aims to identify and profile subgroups of smallholder dairy farmers who share similar adoption status for multiple technologies. Understanding the adoption status and heterogenous characteristics, constraints, and needs of smallholder dairy farmers will provide valuable insights for designing targeted technology dissemination strategies to improve technology adoption rates.

Latent class cluster analysis (LCCA) was used to identify subgroups of smallholder dairy farmers based on patterns in their adoption of multiple dairy technologies. The adoption status of technologies, observed at a point in time, were classified as (1) not aware, (2) aware but no adoption, (3) dis-adoption and (4) continued adoption.[1] These four classifications were adapted from the innovation-decision process conceptualized by Rogers (2003).

In addition to LCCA, a post-hoc analysis of variance (ANOVA) was performed to explore differences between clusters for various relevant characteristics (e.g., individual, household, and farm characteristics) that previous literature identified as variables that help explain various aspects of agricultural technology adoption. This characterization was then used to identify constraints faced by smallholder dairy farmers according to their adoption status of multiple technologies. A descriptive analysis of smallholder dairy farmers' stated reasons for nonadoption and dis-adoption of technologies was also conducted to better understand the smallholders' adoption constraints.

We collected cross-sectional data, including information on the adoption of multiple technologies, from 600 smallholder dairy farming households located in West Java Province, Indonesia. This province contributes 31% of the national fresh milk production and is the location of 18% of smallholder dairy farming households in Indonesia (Statistics Indonesia, 2015, 2021). Similar to other developing countries experiencing rapid economic growth, structural transformation, and growing demand for dairy products, most dairy farms in Indonesia are small-scale and are generally characterized by poor dairy feed quality, low dairy hygiene, and various animal health issues (FAO, 2022; Knips, 2005; Ngeno, 2018; Priyanto & Rahmayuni, 2020).

The LCCA results identified two unique clusters or segments of smallholder dairy farmers that are mainly differentiated by their technology awareness and adoption status. The clusters reflect the common technology adoption status of farmers and highlight the unique constraints faced by each cluster in adopting dairy technologies. One segment of dairy farmers is particularly disadvantaged with respect to having access to information. In some cases, even when they have the necessary resources to invest in the dairy farming technology, complexity and lack of access to other inputs prevent them from adopting technologies. Our results provide insights into the challenges faced by smallholder dairy farmers at different stages of the technology adoption process, and inform the design of technology dissemination programs targeted at smallholder dairy farmers.

Section 2 describes the key features of the dairy farming sector in Indonesia. Section 3 explains the adoption status classifications considered in this study. Section 4 presents the method that includes information about the survey and the estimation strategies. Section 5 presents the results, followed by the discussion in Section 6. Finally, Section 7 concludes the results and the implication of the study.

[1]Adoption status is derived from a series of questions with binary responses, as depicted in Figure 1.

2 | STUDY SETTING

Smallholder dairy farmers in Indonesia face various constraints that limit their ability to adopt farm management practices and improved dairy farming technologies to take advantage of market opportunities. These constraints include relatively low milk production per cow (less than 10 L per cow/day)[2]; poor milk quality (due to unhygienic milking and milk handling practices); limited access to inputs (e.g., quality feed and water), capital and finance; and institutional barriers (e.g., quality standards) (Morey, 2011; Priyanto et al., 2020). Currently, Indonesia meets 77% of domestic milk demand from imported milk, and deficits in domestic milk production are projected to continue to increase (Ministry of Agriculture Indonesia, 2019).

Smallholder dairy production systems in Indonesia are primarily in peri-urban areas. Due to the lack of land for grazing, dairy cattle are typically kept tethered and fed inside a barn, which is often attached to the smallholder dairy farmers' residence. Most smallholder dairy farmers' milk production is for market and sold unprocessed to dairy cooperatives or directly to consumers (small businesses or households). Due to smallholder dairy farmers' small economies of scale, dairy cooperatives have served as an institutional innovation that aims to reduce farmers' transaction costs by collecting and marketing their milk to processing companies. Cooperatives have also aimed to reduce transaction costs by facilitating farmers' access to critical dairy farming inputs and services such as artificial insemination, feed concentrates, milking/production equipment, herd health and cow reproduction services, and access to development and credit programs (Tawaf et al., 2009).

About 60% of dairy farming households in Indonesia are members of dairy cooperatives (Statistics Indonesia, 2015).[3] Members are organized in farmer groups, where these groups facilitate the delivery of assistance and extension programs by cooperatives and development agencies. Additionally, some farmer groups provide services such as loans, facilitate saving schemes, and distribute feed and other dairy farming inputs to their members.

3 | ADOPTION STATUS

Farmers become aware of agricultural technologies through different channels, such as extension programs and information exchange with peers (family and neighbors) (Kathage et al., 2016; Lambrecht et al., 2014). Farmers can conduct trials at their farms or observe the results of trials or adoption by others. Farmers may decide to adopt a technology if the results of these trials (on-farm or by others) are what they expect or may choose not to adopt/dis-adopt if the results are disappointing; however, other factors (e.g. access to complementary technologies) may also influence adoption (Chinseu et al., 2019; Foster & Rosenzweig, 1995). The adoption process is usually nonlinear, involving backward and forward loops, due to the continuous process of learning by doing and from others and changes in technologies' performance, farmers' experiences and needs (Jabbar et al., 2003; Montes de Oca Munguia et al., 2021).

Rogers (2003) conceptualized the innovation-decision process which includes an individual being aware (having knowledge) of a technology, forming favorable or unfavorable attitudes towards adoption, deciding to adopt or reject the technology, implementing the technology, confirming the decision to continue or discontinue adoption after having the experience of using it. In this study, we consider a "snapshot" of this process by classifying adoption status for technologies at a point in time as follows: (1) not aware, (2) aware but no adoption, (3) dis-adoption and (4) continued adoption.

[2]Milk production of dairy cows in developing countries is considerably low compared to dairy cows in more developed countries such as Australia and the United States of America, with average productivity of 21 and 36 L/cow/day respectively (FAO, 2022).

[3]The total number of dairy farm households in Indonesia is 141,989, with almost 60% being members of dairy cooperatives; 17% are not members, possibly because no cooperatives exist in their village, and 19% are not interested in becoming members (Statistics Indonesia, 2015). This suggests that the majority of dairy farm households in Indonesia are cooperative members who can benefit from having better access to dairy farming inputs, extension, and output markets through their membership.

Awareness occurs when a farmer has heard of, has been exposed to and becomes familiar with the technology. Awareness can be considered the first step toward adoption, but does not necessarily lead to adoption because adoption also requires the willingness and the ability to adopt (Fisher et al., 2018; Voss et al., 2021). Factors influencing farmers' awareness of technologies include participation in development and extension programs promoting agricultural technologies, educational levels, participation in collective action,[4] social networks, and distance to markets (Lambrecht et al., 2014). If a farmer has not heard of or has not been exposed to technology, they are unlikely to become familiar with the technology and are therefore in a status of "*not aware*."

After having a certain degree of information about the technology (being aware), farmers may decide to adopt or not to adopt the technology. Farmers who choose not to adopt the technology are referred to as having a status of "*aware but no adoption*." This status could be due to farmers' lack of information, skills and/or capital constraints (Kaliba et al., 2018).

Farmers may adopt the technology to test its suitability (experiment) to their farm and farming system ("aware and adopt"). The technology's characteristics determine the farmers' ability to experiment on their farms. Experimentation may be easier with variable inputs such as high-quality grass varieties and less likely with technologies which require more significant and/or longer-term investments such as building improved drinking water facilities for dairy cows. Farmers may also decide to adopt a technology because they have observed a technology's success in the process of learning from others (e.g., at their neighbor's farm) (Conley & Udry, 2010), which saves them the costs of experimentating with the technology on their own farm.

After farmers become aware, adopt (experiment), and gain experience and information regarding the technology's features relative to their own farming system, farmers are faced with two different options. Farmers may discontinue adopting the technology, that is, reaching a "*dis-adoption*" status, if they are unsatisfied with the results (e.g., inadequate outcomes for the farming system, such as lower than expected yields), and/or if they have problems continuing to access the technology (e.g., lack of financing, discontinued support from development agents, limited availability of the technology, and/or limited availability of complementary inputs) (Chinseu et al., 2019; Grabowski et al., 2016). Conversely, farmers may continue to adopt the technology, that is, reaching a "*continued adoption*" status, if it meets their expectations (e.g., increased productivity, improved quality, lower costs).

4 | METHODS

4.1 | Data and sampling

This study utilized a cross-sectional dataset collected from 600 smallholder dairy farming households located in four main dairy-producing districts in West Java Province, Indonesia. The sampling method was purposive and proportional random sampling. West Java was selected because 31% of national fresh milk production is produced in this region, which is the location of 18% of dairy farm households in Indonesia (Statistics Indonesia, 2015, 2021). Additionally, eight of 14 milk processing companies that source their milk from local dairy farmers are located in West Java (Ministry of Industry Indonesia, 2017). Three of them are significant players in the dairy industry in Indonesia.

The population for this study was all smallholder dairy farming households that were active members of any major cooperative in the four main dairy-producing districts in West Java. In total, there were five cooperatives in which the study drew the sample of smallholder dairy farming households. Of the 26,121 dairy farm households in West Java (Statistics Indonesia, 2015), around 71% of dairy farming households are members of dairy

[4]In this study, collective action refers to activities or actions by a group of smallholder farmers to achieve a common goal. Examples include sharing information on new technologies or farming practices, negotiating better prices for farming inputs or farming outputs.

TABLE 1 Distribution of respondents by districts

Districts	Farmerpopulation	Initial proportion	Finalproportion	Respondents
Bandung	2860	62.13	50.00	300
Garut	1268	27.55	23.33	140
Cianjur	170	3.69	13.33	80
Bogor	305	6.63	13.33	80
Total	4603	100.00	100.00	600

cooperatives.[5] This is not surprising considering the high level of cooperative membership, particularly among smallholder dairy farmers. Dairy farmers with relatively large dairy farms tend to sell their milk directly to processors and are less likely to be members of dairy cooperatives.

The five cooperatives were located in relative proximity to key urban areas, mainly Jakarta (Indonesia's capital), Bandung and Bogor, where the consumption of fresh milk and other dairy products (e.g., sweet condensed milk) is relatively high compared to other areas in Indonesia (Statistics Indonesia, 2018a, 2018b). A growing number of food service businesses (e.g., cafés, restaurants) located in these cities sell food and beverage products that require fresh and/or high-quality dairy products.

The number of smallholder dairy farming households selected from the districts of Bandung and Garut was proportional to the total population of dairy farms in these districts. As the proportion of farmers in the other two districts, Cianjur and Bogor, was small, we decided to interview at least 80 farmers in each of these districts to be able to compare groups statistically. Dairy farming households were randomly selected from each district according to the proportion or number that had been allocated (Table 1).

4.2 | Survey of dairy farming households

Individual face-to-face interviews with dairy farming household members were conducted between August and September 2017 using a structured questionnaire. The questionnaire was programmed in a mobile-based application, CommCare version 2.36.1 (Dimagi), to improve the efficiency and quality of data collection. The use of CommCare allowed data to be entered and monitored in near real-time.

The questionnaire was refined based on feedback received from pretesting with six dairy farming households which varied in farm size (small: 1–5 cows, medium: 6–10 cows, and large: more than 10 cows). The interviews were conducted by 12 trained enumerators fluent in the local language and with extensive experience conducting farm household surveys in West Java.

The questionnaire compiled information about socioeconomic characteristics of the smallholder dairy farm households, household and farm assets, dairy farm characteristics, milk marketing, access and use of various sources of information and services, adoption status of 12 different dairy farming technologies and management practices related to animal nutrition, health, milk quality and business management, and reasons for nonadoption and dis-adoption of technologies. The "technologies" (listed in Table 2) were chosen after consultation with key stakeholders from government institutions under the Ministry of Agriculture of Indonesia that were involved in research, development, and dissemination of technologies relevant to smallholder dairy farmers, as well as interviews with dairy cooperatives and processors. Stakeholders generally considered these 12 technologies as high priorities for adoption to improve dairy productivity, profitability, and/or milk quality.

[5]Data collected by personal communication with the Indonesian Dairy Cooperatives Union (GKSI) in November 2016.

TABLE 2 Dairy farming technologies and practices

No.	Technologies	Description
	Dairy feed	
1	High protein concentrates (16% or higher)	Concentrates are a feed supplement, generally in the form of pellets or coarse mix, which contain highly nutritious and highly digestible forms of protein, energy, and minerals to support milk production.
2	High-quality grass varieties	High quality grasses that generally require shorter growing time with more yields and better nutritional content (e.g., *Brachiaria brizantha*, *B. Mulato*, and *B. mutica*)
3	Fertilizers to grow grass	Fertilizers (organic and chemical) are used to stimulate grass growth to obtain higher grass yields in a shorter time.
4	Unrestricted access to drinking water	Cows have unrestricted access to drinking water at all times—"24 h a day, 7 days a week."
5	Forage conservation for the dry season (hay, silage)	Conservation of forages consists of a series of techniques and processes to conserve or preserve grasses and forages for a long time. This can be achieved through: (1) drying and compacting (hay) or (2) by lowering the pH (making it acidic) compacting and extracting the air (silage). Hay is obtained by dehydrating the grass through heat and air. Silage is obtained by cutting the grass or forage to a certain size, add some source of energy that can lead to fermentation and in some cases, beneficial microorganisms
	Milk quality-enhancing	
6	Detergents on milking equipment	Use of alkaline and acidic detergents, some of this chlorine-based, to clean the fat and proteins that remain in the containers that are used in the milking and transportation of the milk.
7	Improved milking hygiene to reduce total plate count (TPC)	TPC is a milk quality measure that quantifies the bacteria contamination of milk. To reduce TPC a series of practices and techniques must be adopted, including washing hands with soap before miking or using disposable gloves, cleaning cows' udders, ensuring no water is running down through the udder, and discarding the first few bits of milk accumulated in the teats of the cow because this milk contains a high percentage of bacteria and microorganisms.
8	Stainless steel milking equipment	All utensils that touch the milk should be food-grade quality stainless-steel.
	Animal health	
9	Teat dipping after milking	Self-filling cup with an iodine liquid to prevent mastitis. Each of the four teats is dipped into the cup after milking.
10	Mastitis testing	This test is a practical and fast way to determine if a cow has mastitis. It consists of a pallet with four compartments and a reactive that is mixed with milk from each of the four teats of the udder.
11	Rubber floor mat for the barn/cage	Rubber floor mats are used to protect the cows from cement floors and to prevent lameness.
	Farm management	
12	Record keeping	Writing in a notebook, board, or form, all the data regarding production, reproduction and milk yields, sales, expenses and additional data that come from the dairy business.

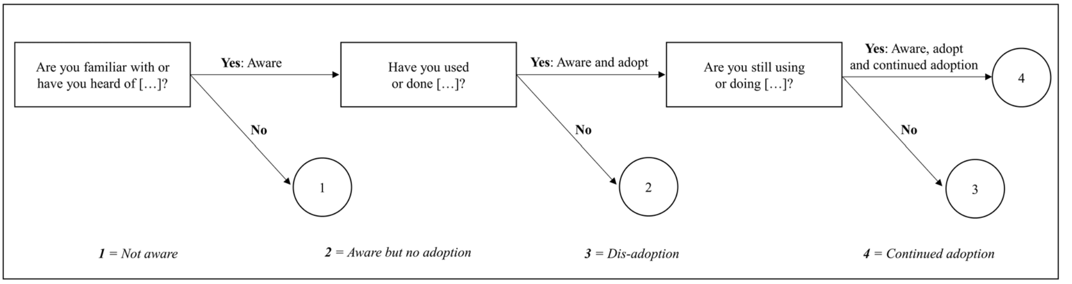

FIGURE 1 Series of questions asked to farmers at the time of survey

To establish farmers' adoption status for these multiple technologies, we asked a series of questions in our survey, as outlined in Figure 1. Dairy farmers were first asked whether they were familiar with or had heard of the technology (aware). If farmers were aware, they were asked whether they had adopted the technology. Lastly, farmers were asked whether they were still using the technology (at the time of the survey) if they indicated they had adopted the technology in the previous question. The binary responses (1 = Yes, 0 = No) to each of these questions were transformed into categorical responses, which are further termed as "*adoption status*": (1) not aware means farmers were not aware/not familiar with the technology (2) aware but no adoption means farmers were aware of the technology but decided not to adopt, (3) dis-adoption means farmers were aware, have used the technology and decided to stop using the technology, and (4) continued adoption means farmers were aware, had used the technology and were still using the technology at the time when we collected the data.

4.3 | Data analysis

4.3.1 | Modeling heterogeneity of adoption processes: LCCA

We used LCCA to profile smallholder dairy farmers based on their adoption status for multiple dairy farming technologies. LCCA is considered the appropriate method given the categorical responses of the 12 technologies analyzed in this study. LCCA is a technique to classify a sample (in this case, smallholder dairy farmers) into a set of latent classes or subgroups which share common characteristics. The number of classes or clusters and the proportion of sample members within each cluster are unknown at the beginning (Nylund et al., 2007). This method offers advantages compared to other traditional cluster analysis methods (e.g., K-means method), including (i) selection of the number of clusters is less arbitrary because statistical criteria are used for model selection (e.g., Bayesian Information Criteria), (ii) classification of individuals to classes is probability-based, (iii) insensitivity to differing variances of variables, and (iv) insensitivity to missing data (Magidson & Vermunt, 2002; Schlecht & Spiller, 2012; Vermunt & Magidson, 2005).

LCCA has been employed extensively in the literature, especially in studies that explore sample heterogeneity (Schlecht & Spiller, 2012; Umberger et al., 2015). In the adoption literature, however, to our knowledge, only two studies, Bizimungu and Kabunga (2018) and Jordán and Speelman (2020), have used LCCA to classify farmers. Yet, both studies only considered binary adoption status (adoption and nonadoption).

LCCA classifies the sample by using the set of observed responses, which in this case is the farmers' four adoption status for the 12 technologies. These technology variables are termed as the indicator or "*manifest*" variables, meaning those variables assigned as 1 if the farmers' adoption status to the technology is not aware; 2 for aware but no adoption; 3 for dis-adoption; and 4 for continued adoption.

Following Magidson et al. (2020), the basic formula of the latent class cluster model for categorical variables is as follows:

$$P(y_1, y_2, \ldots, y_{12}) = \sum_{k=1}^{K} P(X = k)P(y_1, y_2, \ldots, y_{12}|X = k)\ldots \quad (1)$$

where $P(X = k)$ is the probability of belonging to a unique latent class k, where $k = 1, 2, \ldots, K$. $P(y_1, y_2, \ldots, y_{12}| X = k)$ is the probability of particular response patterns in the indicator variables (y). Given there are 12 indicator variables, which can be denoted as M_1, M_2, $M_{\ldots}$, M_{12} respectively, implying that $1 \le y_1 \le M_1$, $1 \le y_2 \le M_2$, $1 \le y_{\ldots} \le M_{\ldots}$, $1 \le y_{12} \le M_{12}$, there are $M_1 \cdot M_2 \cdot M_{\ldots} \cdot M_{12}$ possible response patterns. As a result, $P(y_1, y_2, \ldots, y_{12})$ represents the probability of occurrence of a particular response pattern in these indicator variables. Equation (1) reveals that each latent class or subgroup has its own (response patterns) probability $P(y_1, y_2, \ldots, y_{12}| X = k)$ and that the overall probability for the total population is generated as a weighted average of the conditional probabilities using the latent class proportions, $P(X = k)$, as weights. As a result, the population consists of different K unordered (nominal) latent classes. Full details of the LCCA employed in this study are provided in the results section. The LCCA was performed in Latent GOLD 5.1 (Statistical Innovations).

4.3.2 | Characterization of the clusters

An ANOVA was conducted to determine statistically significant differences between the clusters from the LCCA. The variables included in the ANOVA to characterize clusters were informed by the adoption literature, including household and individual socioeconomic characteristics, as well as farm characteristics, such as the number of cows and production information, capital ownership, and access to credit, information, and extension services (Lambrecht et al., 2014; Moser & Barrett, 2006; Ruzzante et al., 2021; Wendland & Sills, 2008).

The null hypothesis was that the mean of each variable was similar across clusters. The only variables discussed in the results section are the key variables that are statistically significant and different between the clusters. The complete list of variables considered in the ANOVA is provided in Supporting Information: Table A3. The characterization of the clusters was performed in Stata 16.0 (Stata Corp).

5 | RESULTS

5.1 | Sample characteristics

On average, dairy farmers were 46 years of age, had completed six years of school, and had 19 years of dairy farming experience. Summary statistics of the sample are presented in Table 3. The dairy farming households had on average four members. Most households (91%) reported that dairy farming was the main income activity for the household. Additionally, 59% of the sample generated income from on-farm nondairy activities (e.g., horticulture and crops), and 39% generated income from off-farm activities (e.g., nonagricultural wage employment, trading and self-employment). On average, dairy farming accounted for 75% of the household income, other farm (nondairy) activities accounted for 11%, and off-farm activities accounted for 14% of household income.

Farmers managed, on average, six dairy cows (lactating and nonlactating cows) and produced 39 L of milk per day and 15 L of milk per cow per day.[6] About 24% of farmers in the sample used credit for dairy farming purposes.

[6]Average milk productivity of the sample is calculated from the reported average production per day from all lactating cows managed by each farm household (i.e., average of the average).

TABLE 3 Summary statistics for the sample of smallholder dairy farming households (n = 600)

Variables	Description	Mean	SD	Min	Max
Age	Age of the respondent (years)	46.24	11.54	21.00	84.00
Education	Education of the respondent (years)	6.44	3.11	0.00	18.00
Experience	Experience in dairy farming (years)	19.08	10.40	1.00	52.00
Household size	Number of people in the household	3.95	1.44	1.00	11.00
Dairy as the main activity	1 = dairy farming is the main income-generating activity of the household	0.91	0.29	0.00	1.00
On-farm nondairy participation	1 = household participated in on-farm nondairy activities	0.59	0.49	0.00	1.00
Off -farm participation	1 = household participated in off-farm activities	0.39	0.49	0.00	1.00
Dairy income	Share of income	0.75	0.23	0.04	1.00
On-farm nondairy income	Share of income	0.11	0.15	0.00	0.78
Off-farm income	Share of income	0.14	0.21	0.00	0.96
Herd size	Total dairy cows managed (including lactating cows, heifers, calves, and bulls)	5.63	5.02	1.00	42.00
Farm milk production	Total farm milk production from lactating cows (L/day)	39.02	35.24	2.00	340.00
Cow productivity	Cow milk production (L/cow/day)	14.75	3.89	2.00	26.25
Dairy farm profit	Dairy farm profit from all lactating cows managed (USD[a]/year)	1964.11	2337.56	−6293.44	19,779.38
Credit	1 = farmer have used credit for dairy farming purposes	0.24	0.43	0.00	1.00
Labor	Total number of hired laborers on the farm	0.35	0.87	0.00	9.00
Distance to cooperative	Distance in minutes	33.35	25.51	2.00	120.00
Distance to farmer group leader	Distance in minutes	6.64	8.14	1.00	120.00
Milk buyers	Number of different buyers milk sold to	1.06	0.24	1.00	3.00
Milk price	Average milk price (USD[a]/litre)	0.31	0.03	0.24	0.55
Familiar with total plate count (TPC)	1 = farmer familiar with the concept of TPC	0.58	0.49	0.00	1.00
Familiar with total solids (TS)	1 = farmer familiar with the concept of TS	0.41	0.49	0.00	1.00
Familiar with fat content	1 = farmer familiar with the concept of fat content	0.57	0.50	0.00	1.00
Familiar with milk density	1 = farmer familiar with the concept of milk density	0.40	0.49	0.00	1.00
Attend meetings with cooperatives	1 = farmer attended meetings with cooperative	0.55	0.50	0.00	1.00

TABLE 3 (Continued)

Variables	Description	Mean	SD	Min	Max
Attend meetings with farmer group	1 = farmer attended meetings with farmer group	0.48	0.50	0.00	1.00
Number of times (in the last 12 months) farmer contacted cooperative extension staff to access information about [...]					
Milk quality	Number of contacts	1.79	3.23	0.00	24.00
Milk yield	Number of contacts	1.18	2.93	0.00	36.00
Information on new technology	Number of contacts	0.09	0.41	0.00	4.00
Value addition	Number of contacts	0.15	1.45	0.00	24.00
Feed supplement	Number of contacts	0.19	1.55	0.00	24.00
Farmer utilized support from cooperative on [...]					
Forages	1 = yes	0.28	0.45	0.00	1.00
Information on new technology	1 = yes	0.43	0.50	0.00	1.00
New management practices	1 = yes	0.26	0.44	0.00	1.00
Government program	1 = yes	0.28	0.45	0.00	1.00
Feed supplement	1 = yes	0.63	0.48	0.00	1.00
Mastitis testing	1 = yes	0.28	0.45	0.00	1.00

[a]Exchange rate 1 USD = 14,459.50 Indonesian Rupiah on July 27, 2018.

Family members served as the primary labor source. On average, farmers sold their milk to more than one buyer (with a maximum of three buyers),[7] with the average milk price paid by their main buyer being USD 0.31/L.[8] Only about one-half of the sample were familiar with milk quality indicators. Farmers frequently attended meetings at their cooperative or with their main farmer group. On average, over the prior 12 months, farmers contacted their cooperative's extension staff three times to access information related to dairy farming. Dairy farmers' utilization of the services provided by the cooperative varied, with the support for feed supplements being the highest (63%). On average, farmers had to travel 33 min to the cooperative office and around 7 min to reach the home of the leader of their main farmer group.

5.2 | Adoption status

Table 4 provides an overview of the adoption status of the 12 dairy technologies for the sample of smallholder dairy farm households. A high share of farmers adopted detergents for washing milking equipment (85%), improving

[7]As cooperative members, farmers' main milk buyer is the cooperative. However, there are a few cases where farmers sell a proportion of their milk to noncooperative buyers (side selling) such as small businesses or directly to other households.

[8]Most of the cooperatives do not have the capacity to conduct individual milk quality testing for farmers. This is despite the milk processing companies testing the milk they buy from the cooperatives, which includes testing milk composition (e.g., fat content or total solids) and bacterial contamination (measured in total plate counts; TPC). There is some variation in how cooperatives test and pay farmers. Cooperative 1 in Bandung district is considerably larger than the other cooperatives in West Java and had support to test the quality of farmers' milk individually. However, most other cooperatives pay a flat rate to farmers (e.g., Cooperative 2 in Bogor district with flat rate of USD 0.35/L) or pay farmers based on group testing (e.g., Cooperative 3 in Bogor district). Further, each cooperative prioritizes different milk quality parameters and this usually depends on which milk processor they sell to. For example, Cooperative 1 is paid a premium based on fat content, whereas Cooperative 2 is paid based on total solids.

TABLE 4 Adoption status of technologies by smallholder dairy farmers (n = 600) (%)

Technologies	Not Aware	Aware but no adoption	Dis-adoption	Continued adoption
Dairy feed				
High protein concentrates (16% or higher)	59.00	21.33	11.67	8.00
High-quality grass varieties	15.83	9.17	1.67	73.33
Fertilizers to grow grass	11.00	14.33	4.50	70.17
Unrestricted access to drinking water	43.00	21.33	0.67	35.00
Forage conservation for the dry seasons (hay, silage)	42.67	44.83	11.17	1.33
Milk quality-enhancing				
Detergents on milking equipment	12.17	2.33	0.83	84.67
Improved milking hygiene to reduce total plate count	14.17	4.17	0.83	80.83
Stainless steel milking equipment	19.50	35.17	3.00	42.33
Animal health				
Teat dipping after milking	41.67	22.67	16.50	19.17
Mastitis testing	59.83	20.00	8.50	11.67
Rubber floor mat for the barn/cage	4.50	33.33	3.83	58.33
Farm management				
Record keeping	53.50	25.67	5.17	15.67

milking hygiene to reduce bacterial contamination (81%), high-quality grass varieties (73%), and using fertilizers to grow grasses (70%). Only moderate numbers of dairy farmers adopted practices to improve drinking water availability, using stainless-steel milking equipment, and laying rubber floor mats.

Between 40% and 60% of farmers were not aware of mastitis testing, high protein concentrates, record keeping, unrestricted access to drinking water, forage conservation for the dry season, and teat dipping after milking. Considering all technologies, the adoption rate of forage conservation was the lowest. Concerning the rate of dis-adoption, the proportion for all the technologies was low (<20%).

5.3 | Results of LCCA: Adoption profile of smallholder dairy farmers

In the analysis, we only included 11 indicator (technology) variables as one of the technologies, detergents on milking equipment, was not significant in the formation of clusters (insignificant p value).

The LCCA estimation involved running latent class models with one to six classes using the 11 technologies as indicator variables. The Bayesian Information Criteria (BIC) was used to determine the model with the best fit (Hagenaars & McCutcheon, 2002; Vermunt & Magidson, 2005). The results suggest that the model with two latent clusters was the optimal solution based on the lowest value of BIC statistics, which generated an improved model with local dependencies among indicator variables (Table 5). All of the 11 indicator variables contributed to the formation of the clusters ($p < 0.05$) (Supporting Information: Table A1). In addition, all of the bivariate residuals (BVR) between pairs of indicators were less than 3.84, suggesting the local dependency assumption of the latent

TABLE 5 Model fit evaluation information

Model	LL	BIC(LL)	Npar	ClassErr
1-Cluster	−6634.63	13595.50	51	0.00
2-Cluster	**−6314.58**	**13172.90**	**85**	**0.07**
3-Cluster	−6241.41	13244.05	119	0.12
4-Cluster	−6188.51	13355.76	153	0.13
5-Cluster	−6148.49	13493.22	187	0.15
6-Cluster	−6116.18	13646.08	221	0.17

Note: The bold values are to show which model is selected from the LCCA (Schlecht & Spiller, 2012).
Abbreviations: BIC, Bayesian Information Criteria; ClassErr, classification error; LL, log-likelihood; Npar, number of parameters.

class model was not violated (Vermunt & Magidson, 2005). Different random seed numbers were also used to check the consistency of this result.

The technology adoption profiles of the two latent clusters generated from the LCCA are presented in Figure 2. Cluster 1 was 57% of the sample (340 farming households), the remainder 43% of the sample (260 households) were in Cluster 2. ANOVA was performed to test differences in each cluster's adoption status patterns for the 11 technologies (Supporting Information: Table A2). Cluster 1 was labeled the "Low awareness/low adoption cluster" due to the significantly higher share of farmers unaware of the technologies and the significantly lower adoption rates among the "aware" farmers. Cluster 1 had a significantly higher proportion of farmers who were not aware of most of the technologies (solid black in Figure 2), and a significantly higher share of the "aware" farmers in Cluster 1 decided not to adopt seven of the technologies: high protein concentrates; high-quality grass varieties; fertilizers to grow grasses; forage conservation; unrestricted access to drinking water; teat dipping; and rubber floor mats (Table 6).

Conversely, Cluster 2 had a significantly higher proportion of overall awareness of all technologies and had a significantly higher proportion of continued adoption for several of the technologies (white bars in Figure 2). Therefore, Cluster 2 is named the "High awareness/high adoption cluster."

It is interesting to consider the diverse reasons behind each cluster's decisions not to adopt specific technologies despite being aware of them (Table 7). Both clusters highlighted high costs of adoption as the main reason for the nonadoption of high protein concentrates, stainless steel milking equipment, rubber floor mats, and forage conservation. However, the reasons for the nonadoption of other technologies extended and varied beyond concerns about high costs. For example, forage conservation, record keeping, teat dipping, and mastitis testing were considered complex to implement by farmers. Additionally, complementary inputs required for teat dipping were reported as unavailable. Satisfaction with current practices and lack of information were additional reasons for nonadoption.

For some technologies, there were nonadoption reasons that were dominant for a particular cluster. For example, a higher share of farmers in Cluster 1 (compared to Cluster 2) did not have enough information to adopt forage conservation, and were satisfied with current practices and therefore did not adopt teat dipping. Farmers in Cluster 2 considered implementing unrestricted drinking water "complex" and reported that they lack information to adopt teat dipping.

In the case of dis-adoption of technologies (Table 8), both clusters said the high cost of high protein concentrates and the limited availability of inputs for teat dipping after milking were the main factors leading to dis-adoption. Again, there were some noteworthy differences observed between clusters. For example, farmers in Cluster 1 responded that the complexity of forage conservation was the main reason for dis-adoption, while farmers in Cluster 2 said the limited availability of inputs and satisfaction with current practices were the main reason. On the other hand, farmers in Cluster 2 dis-adopted record keeping due to its complex implementation, while farmers in Cluster 1 dis-adopted because they were satisfied with their current practice.

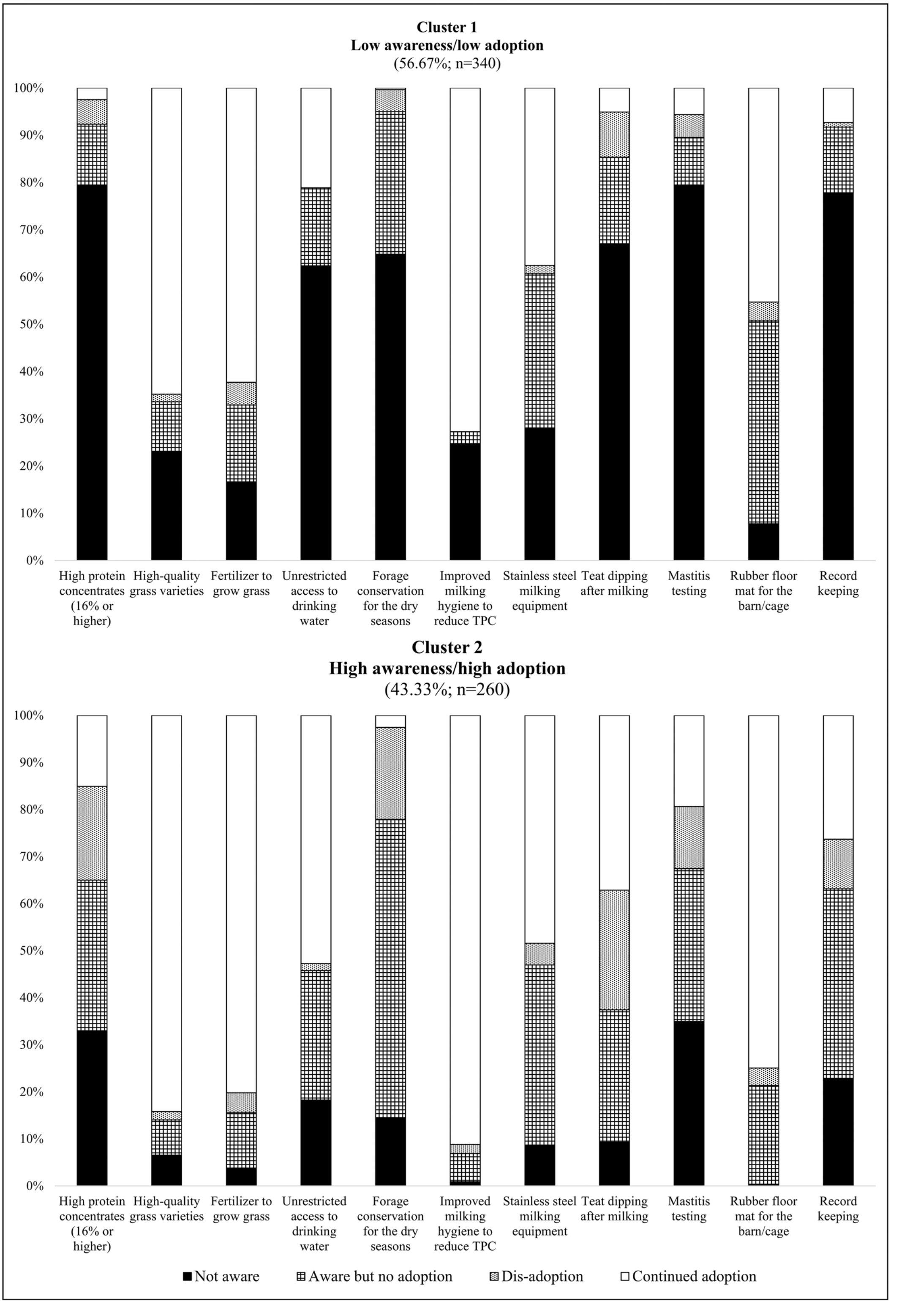

FIGURE 2 Conditional probability of adoption status of multiple technologies for the latent class clusters

TABLE 6 Comparison of farmers who were "aware" but decided not to adopt for each cluster (%)

Technologies	Cluster 1	Cluster 2	Sig.
High protein concentrates (16% or higher)	63.77	47.46	**
High-quality grass varieties	14.18	7.38	**
Fertilizer to grow grass	19.08	12.75	*
Unrestricted access to drinking water	45.60	32.72	**
Forage conservation for the dry seasons (hay, silage)	87.18	73.57	***
Improved milking hygiene to reduce TPC	2.72	6.98	**
Stainless steel milking equipment	45.31	42.02	
Teat dipping after milking	56.88	30.71	***
Mastitis testing	46.97	50.86	
Rubber floor mat for the barn/cage	46.50	20.85	**
Record keeping	61.33	52.94	

Note: *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$ indicate significance at the 10%, 5%, and 1% levels, respectively.
Abbreviation: Sig, significance level from analysis of variance tests.
Percentages are derived from the number of farmers aware but not adopted divided by total farmers who were aware of the technology (including farmers who were aware but not adopted, dis-adopted and continued adoption).

5.4 | Characterization of the latent classes

The key characteristics that are significantly different between the clusters are presented in Table 9. Farmers in the High awareness/high adoption cluster (Cluster 2) were younger, completed higher levels of education, had more experience in dairy farming, and had greater access to labor and financial capital (e.g., credit, profit, and farm assets) when compare to farmers in Cluster 1. In addition, farmers in Cluster 2 sold their milk to a greater number of buyers. They were also more familiar with measures of milk quality.

While farmers in both clusters indicated they intended to increase their production scale (i.e., intended to expand the number of dairy cows), Cluster 2 farmers were more ambitious. They intended to increase their herd size by an average of 11 cows, double the number indicated by farmers in Cluster 1.

Farmers in Cluster 2 were more likely than those in Cluster 1 to participate in group discussions, as indicated by their frequent attendance at cooperative and farmer group meetings. The closer distance to the cooperative office and the home of the farmer group leader may be a reason for Cluster 2's more frequent participation in group meetings. Additionally, farmers in Cluster 2 had a significantly higher number of contacts with cooperative extension staff and a significantly higher utilization rate of the support provided by cooperatives.

6 | DISCUSSION

6.1 | Constraints to technology adoption

This study profiles smallholder dairy farmers based on their adoption status for multiple dairy farming technologies. The LCCA generated two distinct clusters, which are significantly different in their general awareness and adoption levels of technologies. The characteristics of the two clusters further highlight differences in adoption constraints, reflected in differences in individual, household, and farm characteristics, access to information, and reasons for

TABLE 7 Main reasons for farmers' nonadoption despite awareness of technologies (%)

Technologies	Lack of information		High costs		Too complicated		Satisfied with the current practice		Limited availability of input	
	C1	C2	C1	C2	C1	C2	C1	C2	C1	C2
High protein concentrates (16% or higher)	22.73	13.10	65.91	60.71	6.82	8.33	6.82	11.90	13.64	16.67
Unrestricted access to drinking water	7.02	2.82	52.63	53.52	31.58	53.52	22.81	21.13	12.28	7.04
Forage conservation for the dry seasons (hay, silage)	37.25	15.57	35.29	33.53	48.04	47.31	15.69	20.36	9.80	14.37
Stainless steel milking equipment	3.60	2.00	74.77	60.00	4.50	6.00	22.52	25.00	6.31	7.00
Teat dipping after milking	20.97	33.78	27.42	22.97	20.97	21.62	22.58	10.81	25.81	21.62
Mastitis testing	29.03	34.83	12.90	8.99	29.03	26.97	38.71	40.45	0.00	1.12
Rubber floor mat for the barn/cage	5.48	1.85	82.88	79.63	6.16	3.70	17.12	25.93	0.68	3.70
Record keeping	6.38	5.56	0.00	0.00	57.45	62.96	36.17	15.74	0.00	0.00

Note: Percentages: the proportion of farmers in the cluster who responded with reasons (multiple reasons allowed).

Abbreviation: C, cluster.

Technologies that are highly adopted by both clusters are not presented.

TABLE 8 Main reasons for farmers' dis-adoption of technologies (%)

Technologies	Lack of information		High costs		Too complicated		Satisfied with the current practice		Limited availability of input	
	C1	C2	C1	C2	C1	C2	C1	C2	C1	C2
High protein concentrates (16% or higher)	6.25	1.85	62.50	75.93	0.00	5.56	6.25	5.56	18.75	18.52
Forage conservation for the dry seasons (hay, silage)	14.29	13.21	14.29	18.87	50.00	28.30	21.43	33.96	28.57	39.62
Teat dipping after milking	0.00	14.93	25.00	25.37	6.25	19.40	9.38	16.42	46.88	46.27
Mastitis testing	0.00	8.82	5.88	5.88	11.76	0.00	76.47	73.53	0.00	5.88
Record keeping	0.00	3.57	0.00	0.00	33.33	71.43	66.67	17.86	0.00	0.00

Note: Percentages: the proportion of farmers in the cluster who responded with reasons (multiple reasons allowed).

Abbreviation: C, cluster.

Technologies that are highly dis-adopted by both clusters are presented.

TABLE 9 Key characteristics for the latent class clusters

Variables	Cluster 1 (56.67%) Low awareness/low adoption (a)	Cluster 2 (43.33%) High awareness/high adoption (b)	Differences (b−a)	Sig.
Individual, household and farm characteristics				
Age (years)	47.15	45.06	−2.09	**
Education (years)	5.69	7.42	1.73	***
Experience (years)	18.10	20.37	2.27	**
Household size (members)	3.85	4.07	0.22	*
Herd size (cows)	4.39	7.26	2.87	***
Intention to increase production scale (number of additional cows)	5.62	10.61	4.99	***
Farm milk production (L/day)	30.56	50.10	19.54	***
Cow productivity (L/cow/day)	14.42	15.19	0.77	**
Dairy farm profit (USD[a]/year)	1,579.86	2,468.97	889.11	***
Credit (1 = yes)	0.18	0.31	0.13	***
Labor (people)	0.21	0.51	0.30	***
Distance to cooperative (minutes)	36.45	29.32	−7.13	***
Distance to farmer group leader house (minutes)	7.32	5.74	−1.58	**
Marketing and familiarity with milk quality				
Milk buyers (number of buyers)	1.04	1.09	0.05	**
Milk price (USD/litre)	0.30	0.32	0.02	***
Familiar with TPC (1 = yes)	0.45	0.76	0.31	***
Familiar with TS (1 = yes)	0.27	0.59	0.32	***
Familiar with fat content (1 = yes)	0.46	0.70	0.24	***
Familiar with milk density(1 = yes)	0.31	0.52	0.21	***
Group participation, contacts and use of dairy farming services				
Attend meetings with cooperatives (1 = yes)	0.50	0.62	0.12	***
Attend meetings with farmer group (1 = yes)	0.42	0.54	0.12	***
Number of times (in the last 12 months) farmer contacted cooperative extension staff to access information about [...]				
Milk quality (contacts)	1.48	2.18	0.70	**
Milk yield (contacts)	0.97	1.44	0.47	*
Information on new technology (contacts)	0.04	0.15	0.11	***
Value addition (contacts)	0.06	0.27	0.21	*

TABLE 9 (Continued)

Variables	Cluster 1 (56.67%) Low awareness/low adoption (a)	Cluster 2 (43.33%) High awareness/high adoption (b)	Differences (b−a)	Sig.
Feed supplement (contacts)	0.02	0.41	0.39	***
Utilization of support from the dairy cooperative on [....]				
Forages (1 = yes)	0.24	0.32	0.08	**
Information on new technology (1 = yes)	0.35	0.53	0.18	***
New management practices (1 = yes)	0.20	0.34	0.14	***
Government program (1 = yes)	0.21	0.36	0.15	***
Feed supplement (1 = yes)	0.55	0.73	0.18	***
Mastitis testing (1 = yes)	0.16	0.43	0.27	***

Note: *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$ indicate significance at the 10%, 5%, and 1% levels, respectively.
Abbreviation: Sig, significance level from analysis of variance tests.
[a]Exchange rate 1 USD = 14,459.50 Indonesian Rupiah on July 27, 2018.

nonadoption or dis-adoption of technologies. Farmers in Cluster 1 are located farther from information sources, measured by the distance from their dairy farm to the cooperative office and farmer group leader's house. This may explain their higher rate of unawareness of dairy feeding technologies (high protein concentrates, unlimited access to drinking water and forage conservation), animal health technologies (teat dipping and mastitis test), and farm management practices (record keeping).

Despite the resource endowment of farmers in Cluster 2 that may facilitate them to adopt technologies, farmers in this cluster still faced mixed constraints in adopting some technologies. These were reflected by their stated reasons for nonadoption and dis-adoption. Farmers in Cluster 2 reported low adoption of high protein concentrates due to the high cost of the technology. Concentrates with 16% crude protein content or higher are more expensive than the standard concentrates generally provided by the cooperatives, which typically have a crude protein content of less than 13%.

Farmers in Cluster 2 face "complexity" constraints when considering the adoption of forage conservation and record keeping, despite being aware of these practices. The adoption of forage conservation under smallholder farming conditions is labor, time and resource-intensive, and it needs to follow a strict set of guidelines to ensure the quality of the forage (Moran, 2005), suggesting that implementing this technology is also knowledge-intensive. In addition, adopting the practice of record keeping requires farmers to record information about reproduction, production, sales and expenses over time. It requires business skill development to be able to interpret recorded revenue and cost information so that it can be a valuable input for decision-making in the farm business (Gichohi, 2019; Quddus, 2012).

The adoption of mastitis testing in Cluster 2 is considered to be low. Farmers reported limited availability of information and satisfaction with their current practice as the main constraints to mastitis testing. Thus, this suggests a lack of understanding about the benefits of regularly implementing mastitis testing. While the adoption of teat dipping after milking was moderate for Cluster 2, the nonadoption status is divided between aware but no adoption and dis-adoption. The benefits of these technologies may not be directly visible unless cows get mastitis and farmers are aware of the impact that mastitis has on animal health and productivity as well as implications on milk quality. Nell and Schwalbach (2002) conclude that veterinary technologies, like mastitis testing and teat dipping, are only adopted by smallholder dairy farmers when the problems become visible. This implies that farmers are more likely to treat these diseases instead of adopting technologies for disease prevention.

6.2 | Adoption status, constraints, and diffusion strategies

Identifying different adoption status can help determine which kind of interventions are needed given the multilayered constraints and different adoption status of smallholder dairy farmers. Our results suggest the need to consider farmers' heterogeneous constraints and unique production scenarios. Generally speaking, farmers in Cluster 1 are characterized by low awareness of most technologies. Therefore, farmers categorized in Cluster 1 may require "reach-out" strategies to increase their awareness of key technologies and their understanding of potential benefits. Some examples found to be successful in increasing farmers' awareness of agricultural technologies include farmer-to-farmer (F2F) extension and the use of information and communication technology (ICT) (e.g., text/voice messages or short videos) (Cole & Fernando, 2021; Fisher et al., 2018). A similar approach could be implemented in Indonesia to increase smallholder farmers' awareness of the dairy technologies mentioned above by training lead or innovative farmers and encouraging them to share their knowledge with other farmers. Information sharing could also utilize ICT, now easy to access for people in rural areas.

Increasing farmers' awareness of technologies does not guarantee that farmers will adopt the technologies (Fisher et al., 2018; Voss et al., 2021). Farmers may face "*next-step*" challenges after becoming aware of technologies; these can include constraints to capital, skills and availability of inputs, as demonstrated by farmers in Cluster 2. For example, input market failures can prevent adoption of dairy technologies by farmers. Further exploring the reasons inputs are not accessible, affordable, and of consistent quality may be required. If input markets fail, one strategy could be for the government or the private sector (e.g., dairy processors) to work with dairy cooperatives (as the main input provider for farmers) to improve the service provision of critical inputs. These organizations could work together to incentivize farmers to adopt improved milk hygiene practices and other technologies (e.g., teat dipping), which lead to higher quality milk; examples might be individual milk quality testing services and price premiums or discounts based on relevant milk quality parameters.

7 | CONCLUSIONS

The overall results highlight the need for adoption studies to consider different adoption status rather than focusing on a binary status, that is, adoption and nonadoption. This disaggregation allows for a better understanding of the constraints that farmers face. The study emphasizes the importance of considering adoption status of different types of technologies to understand common and specific issues faced by farmers as a group or when adopting specific technologies. The results from this study entail some specific considerations that are required when designing extension programs for smallholder dairy farming households.

The typical extension approach that usually applies a one-size-fits-all standard may not be the best strategy for smallholder dairy farmers. Designing extension strategies that target subgroups of farmers according to their characteristics, adoption status and unique constraints relevant to the technologies will more likely respond to farmers' needs. Further research is required to analyze how such design will result in improved adoption rates of recommended dairy farming technologies.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

Ethical approval for this study was obtained from Human Research Ethics Committee (HREC) at the University of Adelaide with Approval Number: H-2014-188.

ORCID

Rida Akzar http://orcid.org/0000-0002-2800-7330
Wendy Umberger https://orcid.org/0000-0003-4159-7782
Alexandra Peralta http://orcid.org/0000-0001-9338-926X

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AUTHOR BIOGRAPHIES

Rida Akzar is a research fellow at the Centre for Global Food and Resources (GFAR), University of Adelaide. He holds a PhD degree from University of Adelaide (2021). His research interests are on the topic of agricultural technology adoption, rural development, food value chain, and agricultural policy.

Wendy Umberger is a Professor and the Executive Director of the Centre for Global Food and Resources at the University of Adelaide. Wendy specializes in food economics and food policy and has research projects in Australia, North America, Asia, the Pacific Islands and South Africa on the economics of global food systems. Her research uses innovative methods to understand drivers of consumer and producer behavior related to food issues, including nutrition, food safety and health and marketing claims related to quality (credence) attributes associated with the production and processing of food.

Alexandra Peralta is a Senior Lecturer in Agricultural and Food Economics with The Centre for Global Food and Resources (CGFAR) at the University of Adelaide. She is a development economist conducting multidisciplinary research. Alexandra's has experience in economic impact evaluation, lab-in-field experiments, and farmer decision-making models. Her current research projects study the economic and social impacts of mobile finance and smallholder farmers' social networks in Southeast Asia.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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