J. Dairy Sci. 107:2968–2982
https://doi.org/10.3168/jds.2023-23861

Planned behavior, social networks, and perceived risks: Understanding farmers' behavior toward precision dairy technologies

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ABSTRACT

Precision dairy tools (PDT) can provide timely information on individual cow's physiological and behavioral parameters, which can lead to more efficient management of the dairy farm. Although the economic rationale behind the adoption of PDT has been extensively discussed in the literature, the socio-psychological aspects related to the adoption of these technologies have received far less attention. Therefore, this paper proposes a socio-psychological model that builds upon the theory of planned behavior and develops hypotheses regarding cognitive constructs, their interaction with the farmers' perceived risks and social networks, and their overall influence on adoption. These hypotheses are tested using a generalized structural equation model for (a) the adoption of automatic milking systems (AMS) on the farms and (b) the PDT that are usually adopted with the AMS. Results show that adoption of these technologies is affected directly by intention, and the effects of subjective norms, perceived control, and attitudes on adoption are mediated through intention. A unit increase in perceived control score is associated with an increase in marginal probability of adoption of AMS and PDT by 0.05 and 0.19, respectively. Subjective norms are associated with an increase in marginal probability of adoption of AMS and PDT by 0.009 and 0.05, respectively. These results suggest that perceived control exerts a stronger influence on adoption of AMS and PDT, particularly compared with their subjective norms. Technology-related social networks are associated with an increase in marginal probability of adoption of AMS and PDT by 0.026 and 0.10, respectively. Perceived risks related to AMS and PDT negatively affect probability of adoption by 0.042 and 0.16, respectively, by having negative effects on attitudes, perceived self-confidence, and intentions. These results imply that integrating farmers within knowledge-sharing networks, minimizing perceived risks associated with these technologies, and enhancing farmers' confidence in their ability to use these technologies can significantly enhance uptake.

Key words: precision dairy tools, automatic milking system, digitalization in agriculture, theory of planned behavior

INTRODUCTION

Precision dairy tools (**PDT**) in dairy farming measure physiological or behavioral parameters of an individual cow, allow automated detection of changes in these parameters, thus providing timely information to the decision makers, helping them take relevant actions. Some of the important PDT for the dairy sector include automatic milking systems (**AMS**) with measurements such as electrical conductivity and somatic cell counters (for mastitis detection), as well as activity meters (for detection of estrus and lameness) and rumination meters (for detection of irregular feeding patterns) (Steeneveld et al., 2015). These PDT may have important effects on milk productivity, cow and calf health, and management of the farm (Lovarelli et al., 2020). Furthermore, these technologies may help farmers reduce labor costs and increase profitability, although the results related to farm productivity and financial impacts remain mixed in the literature (Bewley et al., 2010; Rutten et al., 2014; Steeneveld et al., 2015).

Given the promise of PDT in improving economic, environmental, and social aspects of sustainability in dairy production systems (see Lovarelli et al., 2020, for an overview), it is important to understand the economic as well as sociopsychological factors that affect uptake of these technologies. However, current literature has mostly focused on explaining the economic rationale behind investment in these technologies (Gargiulo et al., 2018; Rutten et al., 2018; Palma-Molina et al., 2023). Besides socio-economic factors, psychological factors including perceived usefulness and risks related to the behavior as well as the social environment in

Received June 12, 2023.
Accepted November 20, 2023.
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which the decision makers are embedded have been shown as important predictors of behaviors (Foster and Rosenzweig, 2010; Klöckner 2013). However, in the case of PDT, the literature is scant. Therefore, the objective of this study was to understand the role of socio-psychological constructs integrated with economic factors in explaining the intention and behavior related to uptake of PDT on dairy farms.

A widely used approach to elucidate the role of psychosocial constructs behind decision making in the field of economic-psychology is the theory of planned behavior (**TPB**; Ajzen, 1985; De Leeuw et al., 2015; Sok et al., 2021). The TPB proposes that the intention of a behavior acts as a mediator of attitude (individual beliefs related to the outcomes of behavior), subjective norms (individual perception of social pressure), and perceived behavioral control (an individual's opinion or confidence about their ability to carry out a particular behavior; Fishbein and Ajzen, 2011). TPB has also been applied to behaviors related to technology adoption in agriculture (Despotović et al., 2019; Mohr and Kühl, 2021; Yang et al., 2022); however, few studies have applied the full model that includes the link between intention and actual behavior (Yazdanpanah et al., 2014; Meijer et al., 2015; Borremans et al., 2016; Castillo et al., 2021). Although the relationships between behaviors and subjective norm, perceived control, and attitudes are widely documented, it has been pointed out that these aspects may not be enough to capture the social context or environment in which the behaviors are taking place as well as the perceived risks associated with these behaviors (Liao et al., 2010; Castillo et al., 2021).

Therefore, we extend the original TPB framework and integrate farmers' social environment or context (measured through farmers' participation in technology-related social networks) as well as farmers' perceived risks about PDT to answer 2 important questions. First, how do the social networks in which farmers are embedded influence the cognitive constructs related to decision-making and adoption of PDT? Indeed, social networks have been considered important in influencing technology-adoption decisions in various contexts (Maertens and Barrett, 2013; Gardezi and Bronson, 2020; Beaman et al., 2021). Measuring the extent to which technology-related social embeddedness affects cognitive constructs as well as decision making on dairy farms is important to understand the role of informal information-transmission channels in technology adoption. Such information can provide vital policy insights into how these informal information-transmission channels can be leveraged to enhance technology adoption.

Second, this study answers the question on how do perceptions about risks associated with PDT interact with cognitive constructs to predict intentions and behaviors? Risk perceptions related to new technologies or management practices can have important influences on decision making (e.g., Pathak et al., 2019; Li et al., 2020). Understanding and identifying the important negative perceptions associated with PDT can provide a basis for policy development that aims to reduce these negative perceptions so that the uptake of technologies can be enhanced.

MATERIALS AND METHODS

Conceptual Framework and Hypotheses

The TPB provides a basis for the development of a framework that includes social, psychological, and economic factors that influence behavior. We include the 3 main cognitive constructs, *subjective norms*, *perceived behavioral control*, and *attitudes*, that have been shown to influence behavior through their effects on intentions (Ajzen, 1985; Fishbein and Ajzen, 2011). Specifically, subjective norms are defined by how the decision maker weighs the expectations of "important others" (Hansson et al., 2012). Perceived behavioral control can be conceptualized as the individual's opinion about their ability to carry out a particular behavior and can be interchangeably interpreted as a measure of self-efficacy or self-confidence (Ajzen, 1991, 2002). Attitudes can be defined as an individual's beliefs with respect to the outcomes of performing a certain behavior. This basic structure of the original TPB model allows us to test hypothesis 1 (**H1**):

H1: Farmers that have a positive attitude toward PDT, feel social pressure to adopt PDT, and perceive themselves to have the capacity to effectively use PDT are more likely to adopt these technologies.

We extend the TPB framework to include social and economic factors that may complement these cognitive factors in predicting behavior. We integrate 2 additional factors in the TPB framework. First, we include farmers' ability to use and access technology-related *social networks*, which have been previously integrated within the TPB framework in the literature and hypothesized to influence the psychological constructs including subjective norms, perceived behavioral control, and attitudes (Nuthall, 2001; Castillo et al., 2021). Indeed, unobserved cognitive constructs are socially learned and the "original" constructs of TPB (including subjective norms) do not capture the complete dynamics of this social environment (Fielding et al., 2008). Hence, individuals' participation in and ability to access social networks related to digital technologies were integrated to capture these social environment effects. A farmer's social environment or context is created by a social network that functions as a platform for interaction and communication and these interactions affect farmers' beliefs, decisions, and behaviors (Castillo et al., 2021). We recognize that no single construct can fully capture and control for the contextual effects; however, social networks may be one of the more important aspects, especially in predicting technology adoption in agriculture (Maertens and Barrett, 2013; Chavas and Nauges, 2020). Hypothesis 2 (**H2**) underlines the mechanisms through which we conceptualize social networks to have an effect on technology adoption:

H2: Farmers that are part of networks that use PDT feel more social pressure to adopt these tools; however, they will feel more confident while adopting these tools and will likely have a more positive attitude toward these tools.

Additionally, we include perceived risk associated with PDT and hypothesize that perceived risks will have effects on attitudes as well as perceived behavioral control and also direct effects on intention to adopt these technologies. Indeed, perceived risks associated with a "new" technology have been included in TPB frameworks to assess their effect on behavior (Liao et al., 2010; Yazdanpanah et al., 2014). Attitude changes can stem from several sources, but one important source can be subjective assessment of loss of a certain type that can be associated with the adoption of "new" technology. These subjective assessments or risks, in terms of digital-technology adoption in dairy farming, are different from perceived control or self-confidence and could be related to animal health and comfort, work environment, or even data security (Kling-Eveillard et al., 2020; DeLay et al., 2023). Thus, these perceived risks can have effects on perceived behavioral control or self-confidence as well as direct effects on the intentions to adopt a certain behavior (Li et al., 2020). Therefore, we test hypothesis 3 (**H3**):

H3: Farmers that are more worried about the negative aspects or risks associated with PDT will feel less in control and will have a negative attitude toward these tools. Furthermore, these concerns will have a direct negative effect on their intention to adopt.

Figure 1 provides a schematic of the hypothesized relationships and guides the empirical strategy, that is, the generalized simultaneous equation model (**GSEM**) used to test these empirical relationships.

Data and Summary Statistics

Data used in this study were obtained from a sample of dairy farms in Sweden. Consent forms were signed by the respondents before collecting the data for this study. Because data collection was based on informed consent and there was no experimental component to the study, IRB approval was not required. The invitation to participate in the survey was sent to all Swedish dairy enterprises with a registered email address in a database of agricultural enterprises kept by the Swedish Board of Agriculture (n = 2,100). We received 545 complete responses (effective response rate of ~26%). The current dairy population in Sweden comprise around 2,755 dairy farms with an average herd size of 106 cows. Farms that did not have an active email address were not included in the sample because we wanted to interview farmers who indicated at least some use

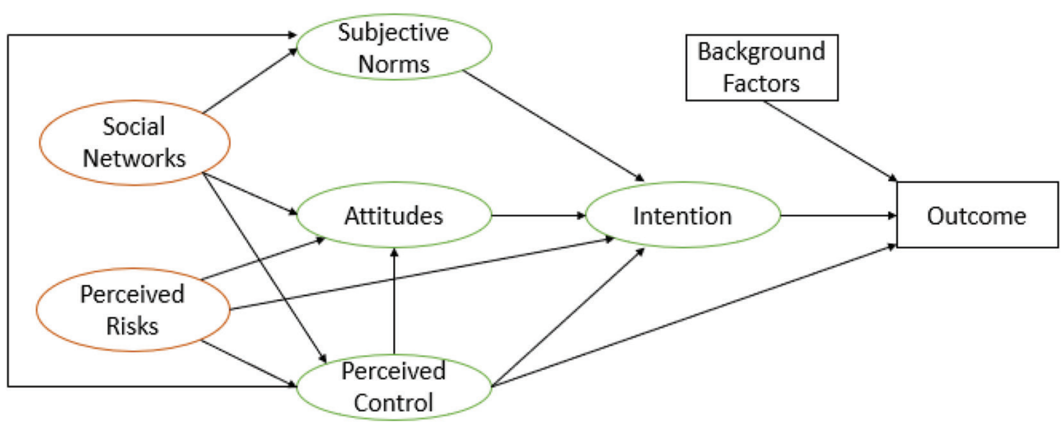

Figure 1. Sociopsychological model of the theory of planned behavior, social networks, and perceived risks. Ovals identify latent variables; rectangles identify directly measured variables.

of digital tools. The effect of this sampling framework on the generalizability of our results and the potential selection bias in our estimates is considered in the Discussion section.

In recent years, freestall housing and AMS has increased and today around 35% of Swedish dairy farms have installed AMS, whereas around 40% have tiestall milking and 25% have milking parlors or rotaries (Växa Sverige, 2022). To ensure confidentiality and respondent anonymity to the researchers, the Swedish Board of Agriculture, without any self-interest in the study, collected the data on behalf of the research group, which only received anonymous data. Data collection took place during December of 2022 and January of 2023 and the survey was distributed via email to all dairy farms with registered email addresses.

The cross-sectional survey focused on collecting data about attitudes, perceived control, subjective norms, intentions, farmers' embeddedness in technology networks (social networks), perceived risks, and background variables (e.g., farmers' age; gender; education; use of extension services, including advice on animal health, feeding, and breeding practices; and the farming system in which the cows are kept). The questionnaire for original TPB constructs, social networks, and perceived risks was developed in line with the recommendations in the literature, though we had to adapt these constructs to fit the context related to PDT (Fishbein and Ajzen, 2011; Li et al., 2020; Castillo et al., 2021). These constructs were subsequently validated in a focus group that included experts from academia, farmers, public sector officers, and extension services agents during a workshop in September 2022. In designing the questionnaire, a 5-point Likert scale was used for all TPB variables, ensuring the principle of compatibility across variables (Sok et al., 2021). The descriptors were strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree.

Two variables were used as outcome variables for the empirical analysis. First, we used our model to test the theoretical hypotheses regarding the adoption of AMS. Second, we modeled the adoption of other PDT (e.g., cell counters, thermal cameras, activity and rumination meters, and so on) for the subsample who already adopted AMS because these tools are usually used in combination with the AMS and are modeled as a count variable.

Table 1 provides the descriptions and summary statistics for outcome as well as background variables for AMS and non-AMS milking systems. Fifty-two percent of the farms in our sample reported the adoption of AMS, 29% reported that they had tiestall milking, and 17% reported that they had parlor milking systems. The farms with AMS in our sample reported to have adopted, on average, 2.43 individual cow sensor technologies, with a minimum of 0 PDT and maximum of 6 PDT, and non-AMS farms reported adoption of, on average, 0.55 PDT. The adoption variable ($ADOPT$) was based on a count of PDT that included (1) cell counters, (2) thermal cameras, (3) feed-intake meters, (4) rumination meters, (5) activity meters, and (6) rumen pH monitors. These sensors can be loosely divided among 3 clusters of management areas within a dairy operation, namely mastitis or udder health management, feed management, and reproductive management technologies.

Feed and reproductive management sensors were reported as adopted by 51% and 47% of the sample, respectively, and mastitis or udder health sensors were reported as adopted by 28% of the farmers. Appendix Table A1 provides details, disaggregated by AMS status, on adoption for all PDT used to construct the $ADOPT$ variable. Activity and feed-intake meters were the most reported adopted technologies in AMS as well as non-AMS herds, possibly because of functions related to estrus detection and monitoring of nutrition, which are especially useful among larger herds. Furthermore, cell counters provide complementary informational input only to AMS herds and thus they are not adopted by non-AMS herds. There may be other udder health monitors, such as conductivity meters, that are not separately investigated here because they were assumed to be part of the AMS functions. Rumen pH monitors and thermal cameras were the least common PDT reported as adopted among the investigated PDT.

Table 1 also shows that AMS farms were generally larger compared with non-AMS farms, with an average herd size of 132 cows compared with 102 cows for non-AMS farms. Furthermore, almost all AMS farms had adopted a freestall system and non-AMS farms had freestall with milking parlor or rotary as well as tiestall systems. Apart from these 2 differences, other aspects such as farmer education, age, or utilization of extension services did not differ significantly among AMS and non-AMS farms.

Empirical Model

In the first step, we performed confirmatory factor analysis on the observed statements from our measurement scale (details provided in Appendix Table A2) to estimate factor scores for latent constructs outlined in Figure 1. These statements are rated on a 5-point scale from strongly disagree to strongly agree, following guidelines and adjustments proposed by Ajzen (1991).

In the second step, we used a GSEM to test the hypotheses regarding the relationship between cognitive and socio-economic constructs and behavioral inten-

Table 1. Data description and summary statistics of Swedish dairy herds participating in the survey (n = 545)[1]

Variable	Description	AMS adopter mean (SD)	AMS nonadopter mean (SD)
ADOPT	Number of sensor technologies adopted by the farm	2.44 (1.28)	0.55 (0.87)
Farm characteristic			
Herd size	Number of dairy cows on the farm	132.7 (109.1)	102.0 (151.4)
Freestall system	Indicator variables = 1 if cows are kept in a freestall system, 0 otherwise	0.99	0.41
Tiestall system	Indicator variables = 1 if cows are kept in a tiestall system, 0 otherwise	0.003	0.56
Other system	Indicator variables = 1 if cows are kept in a combination of freestall and tiestall system or any other system, 0 otherwise	0.003	0.03
Animal health advice	Indicator variable = 1 if the farm received animal health advice, 0 otherwise	0.52	0.34
Breeding advice	Indicator variable = 1 if the farm received breeding advice, 0 otherwise	0.70	0.64
Feeding advice	Indicator variable = 1 if the farm received feeding advice, 0 otherwise	0.78	0.64
Farmer characteristic			
Primary education	Indicator variable = 1 if primary school was the highest education the farmer had attained, 0 otherwise	0.13	0.17
High school education	Indicator variable = 1 if high school was the highest education the farmer had attained, 0 otherwise	0.19	0.27
Agriculture school	Indicator variable = 1 if agriculture school was the highest education the farmer had attained, 0 otherwise	0.44	0.38
Agricultural university	Indicator variable = 1 if agricultural university was the education the farmer had attained, 0 otherwise	0.03	0.03
Other university	Indicatory variable = 1 if university education (other than agricultural university) was the education the farmer attained, 0 otherwise	0.12	0.07
Gender	Indicator variable = 1 if gender of the farmer is male, 0 otherwise	0.71	0.76
Age	Age of the farmer in years	50.6 (11.2)	51.8 (12.2)

[1]Table is divided into herds with automatic milking systems (AMS) and herds with other milking systems (i.e., tiestall, milking parlor, or carousel).

[2]Means of variables are presented for AMS and non-AMS farms. Standard deviations for continuous or count variables are provided in parentheses.

tions and outcomes. Given that the *Adopt* variable is (1) an indicator variable depicting that status of AMS adoption; and (2) a count of smart dairy technologies used on the farm given that AMS is adopted, the GSEM was used with Logistic and Poisson distributions for the outcome equations, respectively. GSEM is a multivariate technique that allows us to estimate the magnitude and statistical significance of the structural relation between observed and latent variables in a theoretical model. The model in Figure 1 can be expressed using the following set of regression equations:

$$PBC = \beta Netw + \beta Risks + \varepsilon_1, \quad [1]$$

$$SN = \beta Netw + \beta PBC + \varepsilon_2, \quad [2]$$

$$ATT = \beta PBC + \beta Netw + \beta Risks + \varepsilon_3, \quad [3]$$

$$INT = \beta ATT + \beta PBC + \beta SN + \beta Risks + \varepsilon_4, \quad [4]$$

$$Adopt = \beta INT + \beta PBC + \beta \mathbf{X} + \varepsilon_5, \quad [5]$$

where ε is the error vector, which represents the error in equations; β represents the statistical relationship between different constructs, and $\mathbf{X}$ is a vector of background factors. Such 2-step models are sometimes referred to as MIMIC models (Anderson and Gerbing, 1988; Owusu-Sekyere et al., 2022). The model outlined in Equation 1 through Equation 5 is our preferred specification (model 4 in the Results section). However, some variations of these models are also reported in the Results section (models 1–3). This is done for 2 purposes. First, this is to illustrate that our point estimates are robust, and the magnitudes or significances of point estimates remain similar across models. Second, these variations of our main model are added to illustrate that our preferred TPB specification indeed has the highest explanatory power among similar models, suggesting that our extension of the base TPB model better captures the key constructs that influence behavior. Sok et al. (2021) recommends testing and reporting these various models to ensure that the extension of the original TPB model is warranted.

The latent constructs included perceived behavioral control (***PBC***), the embeddedness of a farmer in technology-related social networks (***Netw***), perceived risks (***PR***), attitudes (***ATT***), subjective norms (***SN***), and intentions (***INT***). The model was estimated for AMS adoption and then for adoption of digital tools that usually are complimentary to AMS systems. In the adoption equation for both the models, we included background factors, which are in line with the technology-adoption literature related to Swedish livestock production, for example, Owusu-Sekyere et al. (2022), Ahmed et al. (2023). The covariate vector **X** includes dummy variables related to the way the cows are kept; variables on extension services used on a regular basis (related to breeding, animal health, and feeding); herd size; and age, gender, and educational attainment of the farmer.

Furthermore, to assess the consistency and robustness of our structural equation models, as underlined by Kline (2012), we examined (a) the covariation among variables (correlated matrix presented in Appendix Table A3); and (b) if the statistical associations would hold when controlling for other covariates that may be directly correlated with the adoption variable (existence of isolation). In this spirit, several variations of the model Equation 1 through Equation 5 were tested to ensure the robustness of results. Model fit was assessed using likelihood ratio tests across models as well as comparisons of the Akaike information criterion (**AIC**) and Bayesian information criterion (**BIC**) across models. Ideally, to obtain the causal effects of constructs on behaviors, the intentions and behaviors should be measured at 2 different points in time. However, this was not possible given the scope of this project.

RESULTS

Scores for latent variables in Figure 1 were estimated using the confirmatory factor analysis approach. Cronbach's α and Kaiser-Meyer-Olkin statistics (reported in Appendix Table A2) assessed the internal consistency and sampling adequacy, respectively. We found that for most constructs, the Cronbach's α and Kaiser-Meyer-Olkin statistic were above 0.6, implying satisfactory internal consistency and sampling adequacy. For social networks, Cronbach's α was 0.42. However, because the construct was built on only 2 statements (variables), α may not be the best value to test internal reliability of the construct. Therefore, we calculated the raw correlation between the 2 statements, which was 0.30, suggesting a "fair" amount of correlation between the 2 statements. Furthermore, these statistics only indicate the internal reliability of the construct and do not comment on the validity of the construct.

Table 2 and Table 3 show the regression coefficients associated with latent constructs in AMS and PDT adoption regressions, respectively. In both tables (Table 1 and Table 2), model 1 included perceived risks but did not include social networks in the equations. In model 2, the latent construct of social networks was added. In model 3, along with all the latent constructs, background factors were added. In model 4, a direct path of *PBC* was also added because literature has shown that *PBC* may have direct effects on behavior (e.g., Ajzen 2002; Castillo et al., 2021). We observed that the statistical fit, measured through likelihood ratio tests, AIC, and BIC, became better from model 1 to model 3, and model 3 and 4 had similar statistical-fit characteristics (Table 2 and Table 3). In other words, the likelihood ratio test for model selection failed to reject the null hypothesis that model 3 was nested within model 4 and that AIC and BIC were similar for these 2 alterations for AMS as well as PDT adoption regressions. However, the subsequent increase in model fit for model 1 to model 3 in both Table 2 and Table 3 showed that our extended model with additional constructs and covariates can better explain adoption characteristics compared with more basic alterations of the TPB model, suggesting that the extension of original TPB framework was warranted in our case.

Table 4 (columns 2–4) illustrates the direct, indirect, and total impact on the marginal probabilities of adoption of AMS for our preferred specification (model 4 in Table 2). Table 4 (columns 2–4) shows that the original constructs of TPB were statistically significant in explaining AMS adoption behavior, lending support to H1 of our conceptual model; however, the overall effect of *SN* was small compared with *PBC* and *ATT*. A unit increase in *PBC* and *ATT* scores was associated with an increase in adoption of AMS by 0.019 and 0.049 percentage points, statistically significant at 5% and 10% levels of significance, respectively. For the third TPB construct, *SN,* the increase was only 0.009 percentage points (statistically significant at the 5% level of significance). Several studies report a weak relationship between *SN* and *INT*, particularly in farmers (e.g., Kothe and Mullan, 2015; Earle et al., 2020). Indeed, *PBC* moderates the effect of *ATT* and *SN* on *INT*, and a greater *PBC* tends to strengthen the effect of *ATT* and weaken the effect of *SN*, which may explain a relatively weaker role of *SN* in explaining intentions and behaviors (La Barbera and Ajzen, 2020).

Table 4 (columns 5–7) shows the direct, indirect, and total effect on marginal probabilities of adoption of PDT given AMS is already adopted. The qualitative nature of the results did not change compared with AMS adoption model. However, the marginal effects of latent constructs were larger than in the model for AMS

Table 2. Regression coefficients from the generalized simultaneous equation models for adoption of automatic milking systems (n = 540 farms)

Construct[1]	Model 1[2]	Model 2	Model 3	Model 4
Equation 1, *PBC*				
PR	−0.580***	−0.508***	−0.508***	−0.508***
	(0.035)	(0.032)	(0.032)	(0.032)
Netw	—	0.463***	0.463***	0.463***
		(0.042)	(0.042)	(0.042)
Equation 2, *SN*				
PBC	0.597***	0.456***	0.456***	0.456***
	(0.035)	(0.042)	(0.042)	(0.042)
Netw	—	0.408***	0.408***	0.408***
		(0.051)	(0.051)	(0.051)
Equation 3, *ATT*				
PBC	0.747***	0.663***	0.663***	0.663***
	(0.042)	(0.042)	(0.042)	(0.042)
PR	−0.122***	−0.137***	−0.137***	−0.137***
	(0.038)	(0.036)	(0.036)	(0.036)
Netw	—	0.219***	0.219***	0.219***
		(0.043)	(0.043)	(0.043)
Equation 4, *INT*				
PBC	0.171***	0.171***	0.171***	0.171***
	(0.042)	(0.042)	(0.042)	(0.042)
SN	0.315***	0.315***	0.315***	0.315***
	(0.052)	(0.052)	(0.052)	(0.052)
ATT	0.644***	0.644***	0.644***	0.644***
	(0.062)	(0.062)	(0.062)	(0.062)
PR	−0.329***	−0.329***	−0.329***	−0.329***
	(0.047)	(0.047)	(0.047)	(0.047)
Equation 5, *Adopt* (of AMS, Logit model)				
INT	0.622***	0.622***	0.424***	0.337***
	(0.063)	(0.063)	(0.094)	(0.107)
PBC	—	—	—	0.222
				(0.137)
Background factors[3]	No	No	Yes	Yes
Goodness of fit				
Akaike information criterion	7,470.1	7,279.5	7,053.2	7,052.5
Bayesian information criterion	7,547.4	7,369.7	7,203.5	7,207.2
Likelihood ratio test (model 1 vs. model 2)[4]	—	196.59	—	—
		[0.000]		
Likelihood ratio test (model 2 vs. model 3)	—	—	254.28	—
			[0.000]	
Likelihood ratio test (model 3 vs. model 4)	—	—	—	2.67
				[0.102]

[1] *PBC* = perceived behavioral control, *PR* = perceived risk, *Netw* = network, *SN* = subjective norms, *ATT* = attitudes, *INT* = intentions, AMS = automated milking system.

[2] Robust SE are reported in parentheses.

[3] Background factors include age, gender, and education of the farmer; whether the farm receives extension advice regarding feeding, breeding, and animal health; and whether cows are kept in a freestall or tiestall system.

[4] *P*-values for likelihood ratio tests are provided in brackets.

*** indicate statistical significance at 1%.

adoption. Again, the magnitude of the *SN* was smaller than that of the *PBC* and *ATT*. A unit increase in *PBC* and *ATT* scores was associated with an increase in marginal probability of adoption of an additional sensor by 0.194 and 0.081, statistically significant at the 10% level of significance, respectively. For *SN* the increase in marginal probability was 0.049 (statistically significant at the 5% level of significance). Overall, these results also lend support to H1 of our conceptual framework.

Our estimates for adoption of AMS (Table 2) as well as PDT (Table 3) lend support to H2, that is, being embedded in technology networks positively affected the social pressure to adopt PDT (Equation 2), had a positive effect on *PBC* (Equation 1), and improved the *ATT* toward these technologies (Equation 3). A unit increase in *Netw* scores is associated with increases in marginal probabilities of adoption of AMS and PDT by 0.026 and 0.101 (significant at a 1% level), respectively (Table 4, columns 4 and 7). The *Netw* variable comprised statements regarding peer-to-peer learning through social media or farmer groups as well as with support networks when problems related to PDT arise

Table 3. Regression coefficients from the generalized simultaneous equation models for adoption of digital tools (n = 288)

Construct[1]	Model 1[2]	Model 2	Model 3	Model 4
Equation 1, *PBC*				
PR	−0.438***	−0.391***	−0.391***	−0.391***
	(0.045)	(0.042)	(0.042)	(0.042)
Netw	—	0.384***	0.384***	0.384***
		(0.054)	(0.054)	(0.054)
Equation 2, *SN*				
PBC	0.488***	0.332***	0.332***	0.332***
	(0.063)	(0.062)	(0.062)	(0.062)
Netw	—	0.442***	0.442***	0.442***
		(0.066)	(0.066)	(0.066)
Equation 3, *ATT*				
PBC	0.542***	0.463***	0.463***	0.463***
	(0.061)	(0.061)	(0.061)	(0.061)
PR	−0.089*	−0.099**	−0.099**	−0.099**
	(0.049)	(0.047)	(0.047)	(0.047)
Netw	—	0.209***	0.209***	0.209***
		(0.057)	(0.057)	(0.057)
Equation 4, *INT*				
PBC	0.114	0.114	0.114	0.114
	(0.077)	(0.077)	(0.077)	(0.077)
SN	0.221***	0.221***	0.221***	0.221***
	(0.065)	(0.065)	(0.065)	(0.065)
ATT	0.466***	0.466***	0.466***	0.466***
	(0.077)	(0.077)	(0.077)	(0.077)
PR	−0.287***	−0.287***	−0.287***	−0.287***
	(0.060)	(0.060)	(0.060)	(0.060)
Equation 5, no. of digital tools (Poisson)				
INT	0.105***	0.105***	0.109***	0.088**
	(0.020)	(0.020)	(0.032)	(0.036)
PBC	—	—	—	0.045
				(0.042)
Background factors[3]	No	No	Yes	Yes
Goodness of fit				
Akaike information criterion	4,332.6	4,237.9	4,086.0	4,086.8
Bayesian information criterion	4,398.5	4,314.9	4,214.2	4,218.7
Likelihood ratio test[4] (model 1 vs. model 2)	—	100.61	—	—
		[0.000]		
Likelihood ratio test (model 2 vs. model 3)	—	—	179.98	—
			[0.000]	
Likelihood ratio test (model 3 vs. model 4)	—	—	—	1.19
				[0.275]

[1]*PBC* = perceived behavioral control, *PR* = perceived risk, *Netw* = network, *SN* = subjective norms, *ATT* = attitudes, *INT* = intentions.

[2]Robust SE are reported in parentheses.

[3]Background factors include age, gender, and education of the farmer; whether the farm receives extension advice regarding feeding, breeding, and animal health; and whether cows are kept in a freestall or tiestall system.

[4]*P*-values for likelihood ratio tests are provided in brackets.

***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

(Appendix Table A2). These results showed that informal channels of information transmission may be important in diffusion of technologies.

Regression estimates in Table 2 and Table 3 also support H3, that negative perceptions about these technologies decreased *PBC* (Equation 1) as well as *ATT* (Equation 3), and had an overall negative effect on *INT* (Equation 4). A unit increase in the *Risks* score was associated with decreases in marginal probabilities of adoption of AMS and PDT by 0.042 and 0.16 (statistically significant at a 1% level of significance), respectively (Table 4, columns 4 and 7). The perceived risks elicited through the questionnaire were related to (1) discomfort associated with wearing or using PDT, (2) safety of data generated from PDT, (3) negative effect of PDT on animal–human relationship, and (4) costliness of adopting PDT. The stacked bar chart in Appendix Figure A1 shows that, except for the costliness of PDT, all other aspects asked in the questionnaire were of considerable concern to the farmers. About 72% of the respondents agreed that wearing or using PDT can be a significant source of discomfort and pain for the animal. Sixty-nine percent of the respondents considered data intrusion and lack of private data safety to

Table 4. Direct, indirect, and total effects (marginal probabilities; SE are reported in parentheses) from model 4 of automated milking system (AMS; Table 2) and precision dairy tool (PDT) adoption regressions (Table 3)

	AMS adoption effect			PDT adoption effect		
Construct[1]	Direct	Indirect	Total	Direct	Indirect	Total
INT	0.042***	—	0.042***	0.210***	—	0.210***
	(0.012)		(0.012)	(0.036)		(0.036)
PBC	0.028	0.020**	0.049***	0.114	0.080***	0.194***
	(0.017)	(0.008)	(0.014)	(0.075)	(0.029)	(0.039)
SN	—	0.009**	0.009**	—	0.049**	0.049**
		(0.004)	(0.004)		(0.020)	(0.020)
ATT	—	0.019**	0.019**	—	0.081***	0.081***
		(0.007)	(0.007)		(0.030)	(0.030)
Netw	—	0.026***	0.026***	—	0.101***	0.101***
		(0.006)	(0.006)		(0.027)	(0.027)
PR	—	−0.042***	−0.042***	—	−0.159***	−0.159***
		(0.009)	(0.009)		(0.036)	(0.036)

[1]*INT* = intentions, *PBC* = perceived behavioral control, *SN* = subjective norms, *ATT* = attitudes, *Netw* = network, and *PR* = perceived risk.
*** and ** indicate significance at 1% and 5%, respectively.

be a significant risk, and approximately 40% thought that PDT can have negative consequences on human–animal relationships.

In summary, *ATT*, *PBC*, and *SN* had significant indirect effects on adoption behavior, and these effects were mediated through intentions. Furthermore, embeddedness in technology networks was positively and indirectly associated with adoption of AMS as well as other PDT, and these effects were mediated through *SN*, *ATT*, and *PBC*. Similarly, perceived risks had negative indirect effects on adoption behavior in both models and these effects were mediated through *PBC* and *ATT*, as well as through *INT*.

DISCUSSION

This study contributes to the literature on adoption of PDT in 2 ways. First, as far as we know, this is the first study that models the sociopsychological aspects related to adoption of PDT and contributes to the understanding of farmers' motivations to invest in these technologies. Second, we propose an integrated model that includes farmers' embeddedness in technology-related social environments and perceptions of risks related to PDT within a TPB framework. This model was used to develop hypotheses regarding the relationships between the original and extended constructs as well as their relationship with adoption behavior. We illustrate that perceived risks and farmers' social context have a significant bearing on cognitive constructs as well as intentions and better predict behavior compared with models where these aspects are not considered. Findings indicate that technology firms can enhance their sales by focusing on ameliorating the perceived risks associated with these technologies. Key negative perceptions associated with PDT were identified as risks related to privacy of data, discomfort of animals, and negative effects of PDT on animal–human relationships. In addition to ameliorating the perceived risks associated with PDT, our results imply that strengthening interaction between networks of users and nonusers of PDT can enhance adoption through its positive effect on subjective norms, attitudes, and perceived control.

Several authors have highlighted the need to connect an individual's cognitive processes with the environment in which a decision maker is embedded (Edwards-Jones, 2006; Castillo et al., 2021). Indeed, information frictions are important constraints to adoption of new technologies and social relationships can serve as important channels through which individuals learn about, and are then convinced to adopt, new technologies (Beaman et al., 2021). Our model, in line with previous literature, shows that TPB constructs act as mediators to farmers' embeddedness in technology-related social networks and illustrates how the internal (cognitive) and external (social networks) factors interact together to explain behavior. Such social networks can provide access to more and better information (Wuepper et al., 2018); thus, they may have important effects on attitudes, perceived control, and subjective norm and through their effects on these cognitive constructs have an impact on intentions and behaviors. Indeed, our results show that farmers' embeddedness in social networks has a positive impact on *ATT*, *SN*, and *PBC*, and thus on behavior. Our results suggest the need to identify strategies that can maximize social learning about these technologies and thus maximize diffusion. Extension services as well as outreach events organized by technology companies can enhance farmer-to-farmer contact to strengthen these technology-related social networks.

Similarly, perceived risks (which are measured as subjectively determined expectation of a certain type of loss) have been shown to affect behavior (Liao et al., 2010; Quintal et al., 2010). We hypothesize that these negative perceptions about PDT can indirectly affect behavior through their negative effects on attitudes, perceived behavioral control, and intentions. Our results show that the subjectively assessed negative perceptions about technologies have crucial final impacts mediated through TPB constructs. Our descriptive results indicate that the main concerns related to PDT are about animal welfare and discomfort due to PDT, data intrusion and lack of private data safety, and perceptions about negative consequences on human–animal relationships. Therefore, aspects of animal welfare, data privacy and safety, and the effects on human–animal relationships must be considered in the development of PDT. This suggests that technology companies (through development of animal-friendly and data-secure products) as well as advisory services (through elucidating best practices associated with PDT) can play an important role in alleviating these negative perceptions about PDT.

Key policy implications regarding digitalization of the dairy sector can be derived from our case study on Swedish dairy production. First, changes in perceived social pressure regarding PDT may not have substantial effects on digitalization. However, strengthening self-confidence and a positive change in attitudes toward PDT can positively and substantially affect digitalization of animal-farming sectors even in absence of financial incentives. Second, initiatives that increase the "embeddedness" of decision makers in technology-related networks that allow for peer-to-peer transfer of knowledge and learning can positively affect cognitive constructs that play a central role in technology acceptance and adoption. Third, technology firms and extension services can actively focus on reducing the negative perceptions related to PDT (including negative perceptions about animal discomfort, data privacy, and animal–human interactions), which would in turn improve farmers' attitudes toward these technologies and increase their perceived self-confidence about adopting more PDT. In our context, strengthening social networks and reducing perceived risks related to PDT may be more important than improving subjective norms related to PDT.

There are a few concerns related to the generalizability of our estimated impacts. The first concern is related to our sampling strategy, which relied on contacting the farmers through emails, thereby enhancing the representation of farmers who are perhaps already more technology friendly. Furthermore, the topic of the survey could also induce some selection bias because farmers with more positive attitudes toward digital technology could be more inclined to participate in the survey. A second concern is that the respondent group in this survey differed in some key aspects in relation to the average Swedish dairy farmer. Both AMS and non-AMS respondents were younger (51–52 yr) compared with the national Swedish average (59 yr). Furthermore, the respondents with AMS also had a larger herd size, 132 cows, compared with the national average of 106 cows per herd. Indeed, farms with greater herd sizes adopt more PDT (Gargiulo et al., 2018). Furthermore, about one-third of the Swedish dairy herd population has fewer than 50 cows, and a majority of these use tiestall milking, which affects both the Swedish average and the average of non-AMS herds of this study. Our sampling framework and the key differences of our sample with national herd characteristics may imply that the self-reported constructs and intentions to adopt may not correctly represent the average Swedish dairy farmer and can potentially bias our estimates on the effect of latent variables on behavior. Future research should ameliorate concerns related to incomplete sampling and deepen the understanding of adoption of PDT using cross-country and panel data.

CONCLUSIONS

This study provides novel insights into the decision-making processes and elaborates on the role of cognitive constructs, farmers' perceptions, and farmers' social context in technology-adoption decisions. We find that decisions are a result of an interplay between cognitive factors (such as TPB constructs) and environmental factors (such as the technology networks in which farmers operate), and thus these external factors need to be considered in the promotion of digitalization of agriculture in various contexts. Furthermore, as subjective assessments of the negative effects of PDT can vary significantly among farmers and have a bearing on farmer behavior, having a better understanding of what these negative perceptions are, as well as alleviation of these concerns, can lead to increased adoption of PDT.

ACKNOWLEDGMENTS

The authors acknowledge funding from the Swedish Research Council for Sustainable Development (FORMAS, Stockholm, Sweden; grant number 2021-02348). Author contributions are as follows: Haseeb Ahmed, conceptualization, methodology, formal analysis, data curation, writing (original draft and review and editing), and funding acquisition; Lisa Ekman, writing (review and editing), project administration, funding acquisition, and supervision; Nina Lind, writing (review and editing), methodology, funding acquisition, and supervision. The authors have not stated any conflicts of interest.

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APPENDIX

Table A1. Means for adoption of precision dairy tools among automatic milking system (AMS) and non-AMS herds

Variable	Description	Mean for AMS adopters	Mean for AMS nonadopters
Cell counters	Indicator variable = 1 if the farm adopts a cell counter (Bacticam [Agricam], Herd Navigator [Delaval], and so on), 0 otherwise	0.54	0
Activity meters	Indicator variable = 1 if the farm adopts an activity meter, 0 otherwise	0.69	0.25
Rumination meters	Indicator variable = 1 if the farm adopts a rumination meter, 0 otherwise	0.40	0.09
Feed monitors	Indicator variable = 1 if the farm adopts concentrate or roughage intake meters, 0 otherwise	0.62	0.19
Thermal camera	Indicator variable = 1 if the farm adopts a thermal camera, 0 otherwise	0.003	0.01
Rumen pH monitors	Indicator variable = 1 if the farm adopts a rumen pH monitor, 0 otherwise	0.003	0.003

Table A2. Constructs and factor analysis

Construct	Mean (SD)	Factor loadings	Cronbach's α	KMO[1]
Attitude			0.70	0.76
I think adoption of digital tools is, to some extent, necessary for optimizing the productivity of my farm.	3.82 (0.99)	0.81		
In my opinion, information from digital tools is an important factor for developing our company.	2.81 (1.25)	0.34		
There is no reason for me to invest in more digital tools than the ones I have.	3.46 (1.10)	0.68		
I like to try new digital tools to improve my farm production processes.	3.95 (0.99)	0.71		
Information from these digital tools makes it easier to make decisions regarding the health and well-being of my cows.	2.69 (1.33)	0.79		
Subjective norm			0.67	0.74
I feel that my family encourages me to increasingly use digital tools on my farm.	3.14 (1.09)	0.51		
I think my peers and other farmers I know increasingly rely on digital tools for dairy farm management.	3.65 (0.84)	0.45		
On-farm advisers approve of the use of digital tools for my farm management.	3.49 (0.96)	0.72		
When I think about investing in a digital tool, I investigate how other farmers' experiences of that specific tool is.	3.87 (0.95)	0.77		
I believe that the accessibility of local service technicians affects my choice of digital tools.	3.63 (1.06)	0.82		
Perceived behavioral control			0.66	0.66
I think it is easy to find information on how to use my dairy digitalization tools in my daily work.	2.58 (1.02)	0.31		
I find it difficult to interpret the information from my digital tools.	3.82 (0.98)	0.74		
I believe that the data generated from my digital tools helps me to reduce costs and increase efficiency on my farm.	3.25 (1.13)	0.34		
I find it difficult to stay up to date with the rapid development of digital tools within dairy production.	3.67 (1.05)	0.75		
I almost always know where to turn when I encounter problems with my digital tools.	4.03 (0.96)	0.66		
Social network			0.42	0.5
I have a network where I can exchange experiences and knowledge related to digital tools (for example in an ERFA group, a Facebook group, or similar).	3.47 (1.06)	0.41		
I feel like I have a network to whom I can reach out to get support when I encounter problems related to digital tools.	3.19 (1.04)	0.41		
Perceived risk			0.71	0.72
I think digital tools make dairy farming more costly.	2.19 (1.15)	0.71		
I think digital tools negatively affect human–animal relationships.	2.68 (1.17)	0.74		
I feel confident that the data produced on my farm can be kept safe, so that the risk of, for example, data intrusion can be minimized.	1.99 (0.97)	0.63		
Some digital tools and gadgets can be painful or stressful for the animals.	3.81 (0.98)	0.68		
Intention			0.87	0.93
One of the main reasons to adopt digital tools is to maximize production (profit intention).	3.77 (0.91)	0.77		
Digital tools help me decrease farming costs (profit intention).	3.98 (1.01)	0.81		

Continued

Table A2 (Continued). Constructs and factor analysis

Construct	Mean (SD)	Factor loadings	Cronbach's α	KMO[1]
Digital tools help me minimize disease losses by generating timely alerts (profit intention).	4.00 (0.93)	0.76		
One of the main reasons to adopt digital tools is to improve animal health and welfare (animal welfare intention).	3.77 (0.98)	0.68		
Digital tools help me minimize health risk and suffering for my cows through timely alerts (animal welfare intention).	3.84 (1.04)	0.83		
One of the main reasons to adopt digital tools is to improve the working conditions at my farm (better work environment intention).	3.85 (1.02)	0.80		
I use digital tools because they make day-to-day decision-making easier and effective (better work environment intention).	3.16 (1.15)	0.62		
Digital tools can make my work stressful because they generate a lot of data and alerts (better work environment intention).	2.97 (1.14)	0.13		
I use digital tools to be able to manage the herd in a more flexible way, for example, to be able to monitor and manage the herd, even if not on site (better work environment intention).	3.71 (1.16)	0.73		
I use digital tools to become more efficient when reporting mandatory herd data to authorities and other organizations (e.g., dairies, slaughter house; better work environment intention).	3.73 (1.09)	0.44		

[1]Kaiser-Meyer-Olkin statistics.

Table A3. Pearson correlation matrix

	Variable[1]	1	2	3	4	5	6	7	8	9	10	11	12	13
1	*Netw*	1												
2	*PR*	−0.20*	1											
3	Primary education	0.05	0.13*	1										
4	High school education	−0.003	0.01	−0.11*	1									
5	University education	0.02	−0.02	−0.06	−0.24*	1								
6	Housing system	−0.21*	0.34*	0.06	−0.04	−0.04	1							
7	Milking system	−0.22*	0.35*	0.07	−0.05	−0.07	0.84*	1						
8	Animal health advice	0.06	−0.18*	−0.08	−0.02	0.06	−0.17*	−0.19*	1					
9	Breeding advice	0.18*	−0.12*	−0.03	0.07	0.004	−0.07	−0.07	0.26*	1				
10	Feeding advice	0.12*	−0.21*	−0.07	0.07	−0.02	−0.20*	−0.21*	0.31*	0.42*	1			
11	Gender	0.009	−0.04	0.14*	0.17*	−0.21*	0.01	0.02	0.005	0.02	0.02	1		
12	Age	−0.01	0.001	0.11*	−0.05	−0.12*	0.12*	0.11*	−0.005	−0.004	−0.11*	0.04	1	
13	Herd size	0.07	−0.07	−0.03	0.03	−0.02	−0.13*	−0.08	0.10	0.05	0.06	−0.05	0.002	1

[1]*Netw* = network, *PR* = perceived risk.

*Indicates statistical significance at 1% level.

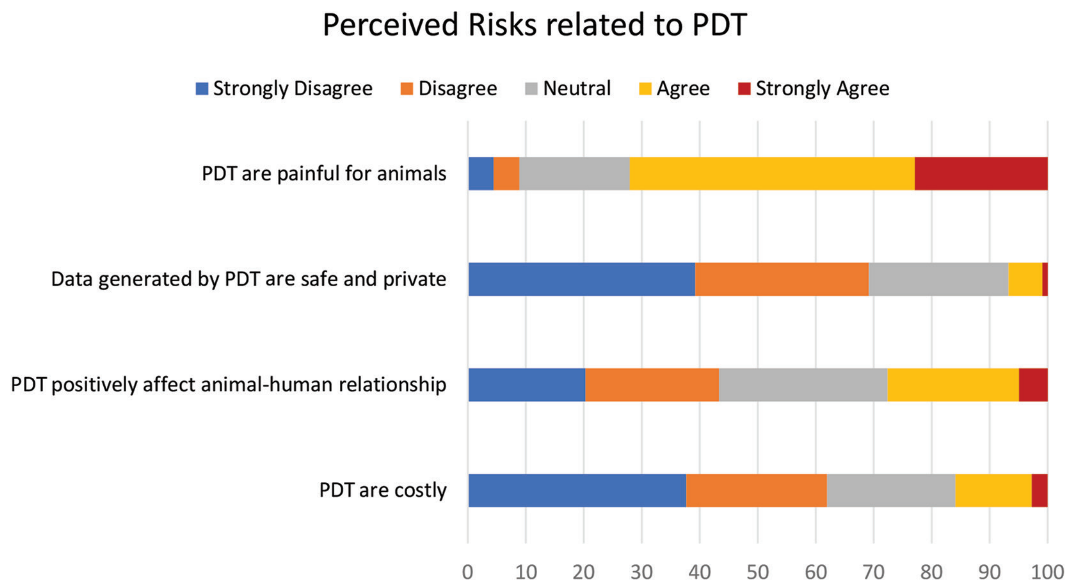

Figure A1. Perceived risks related to precision dairy tools (PDT).