ADOPTION OF HERD MANAGEMENT SMARTPHONE APPS IN GERMAN DAIRY FARMING

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GEWISOLA

2019

Vortrag anlässlich der 59. Jahrestagung der GEWISOLA
(Gesellschaft für Wirtschafts- und Sozialwissenschaften des Landbaues e.V.)

1. ***„Landwirtschaft und ländliche Räume im gesellschaftlichen Wandel“***
Braunschweig, 25. bis 27. September 2019

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Abstract

There has been a steady increase in decision support tools available for farmers including dairy herd management smartphone apps. The existing literature does not yet cover topics concerning the adoption and use of herd management smartphone apps or which specific functions of such apps are perceived as most useful by dairy farmers. It is unclear if technology adoption can only be explained by economic reasoning, as the beliefs about a technology also play a role in decision making. Therefore, this study seeks to determine whether an extended Technology Acceptance Model can explain adoption and use of herd management smartphone apps. Results about the adoption and use of dairy herd management smartphone apps are derived from an online survey conducted in 2018 with 280 German dairy farmers. To model farmers' frequency of herd management smartphone app use, we applied partial least squares structural equation modelling and an ordered logit model. Our results show that 93% of the dairy farmers in our sample use a smartphone and 61% already use a herd management smartphone app. Daily use is reported by 38% of the adopters. Dairy farmers rated functions related to the observation of animal health, reproduction management and data gathering as most useful, which should be in focus by developer and providers for future development. The key attitudinal components of the Technology Acceptance Model, namely perceived ease of use and perceived usefulness, both positively influence the intention to use such apps. This ultimately has a positive effect on the actual usage behavior. Besides other factors, dairy farmers' education and knowledge of herd management smartphone apps have a positive effect on perceived ease of use. Our model explains 33% of the variance in the actual usage behavior related to herd management smartphone apps. Since perceived ease of use and perceived usefulness positively influence the intention to use such apps and ultimately the actual usage behavior, developers and providers should highlight the benefits of using herd management smartphone apps and also keep the interface of the apps as simple as possible.

Keywords

Herd management smartphone app, German dairy farmer, Partial least squares structural equation modelling, Technology acceptance model

1 Introduction

Herd management practices are of great importance for the productivity of dairy farms (EL-OSTA and MOREHART 2000). As dairy herd sizes increase, herd management becomes more and more difficult and time consuming for a dairy farmer (GARGIULO et al. 2018). Insufficient herd management can result in reduced animal welfare and health which can lower cow performance and harm the economic status of the dairy farmer (CALSAMIGLIA et al. 2018). Identifying changes in physiological parameters enables a dairy farmer to intervene and ensure animal health (BEWLEY 2010). Furthermore, record keeping and evaluation at cow level are considered to be essential for monitoring herd performance and making effective herd management adjustments if necessary (BARRAGAN et al. 2016). However, shifting from management of the herd as whole to management of the individual cows within the herd is contingent on the collection and evaluation of data in (near) real time (DEBAUCHE et al. 2018).

Recent developments in smartphone technology, access to mobile internet and cloud services have led to an increase in the number of smartphone apps supporting farmers' decision making (ROSE et al. 2016). Smartphones and associated apps can be used in connection with other precision agricultural technologies or independently. Furthermore, smartphone apps fit well into the working routine of farmers due to their mobile character.

The use of smartphones might also enhance a dairy farmer's decision making and even the adoption and use of data driven precision dairy technologies. For instance, herd management smartphone apps, as a form of Decision Support Tool (DST), can be used to enter and assess cow individual data (ABDELSAYED 2017). Monitoring cows via smartphone apps can provide essential information on their health or reproductive status as well as their feeding, lying and moving behavior in real time (DEBAUCHE et al. 2018). Sensing technology and real-time monitoring combined with smartphones and associated apps enable a dairy farmer to react faster and allow for improved decision making in livestock management (KAMILARIS and PITSILLIDES 2016). Furthermore, they can aid as an early warning system if cows' behavior changes. The combination of smartphone apps with stationary management systems and precision dairy technologies can additionally allow a dairy farmer to review and enter individual animal data from anywhere at any time (HERD 2014).

While the adoption of various precision dairy technologies by dairy farmers to improve production on dairy farms has been studied (e.g. GARGIULO et al. 2018), information about the implementation of smartphone based DST in herd management is currently very limited since most studies focus on the technological side (e.g. DEBAUCHE et al. 2018). To assess the adoption and use of herd management apps by dairy farmers, we empirically test an extended version of the Technology Acceptance Model (TAM). While the original version of the TAM focuses only on the decision to adopt a technology or not (DAVIS 1989), we include the use frequency of smartphone herd management apps as the endogenous variable to further differentiate adoption behavior. Without assessing the potential usefulness or value a DST has for a farmer, adoption and usage will remain low (Evans et al. 2017). Therefore, we also wanted to identify which herd management smartphone app functions dairy farmers perceive as useful. This is the first study to focus on adoption and use of smartphone herd management apps in dairy farming. The process of adoption, in particular the motives of adoption and the perceived usefulness of technology functions from a farmers' point of view are of high interest for developers and providers of smartphone apps.

2 Main body

2.1 Theoretical Framework

Innovation adoption is regarded as inevitable if there is a clear advantage and adoption is rather effortless. However, these conditions almost never hold true for technological innovations. Moreover, it has been shown that decisions on innovation adoption are not only based on proposed economic advantages (MCDONALD et al. 2016).That is why focusing on attitudes and beliefs of farmers could substantially contribute to understanding farmers' adoption decisions (AUSTIN et al. 1998). The TAM is the most widely applied model for technology adoption which focues on attitudes and beliefs (VERMA and SINHA 2018) and has also been used in the dairy sector (e.g. SCHAAK and MUßHOFF 2018). Our proposed TAM and its extensions for herd management smartphone app adoption are graphically displayed in Figure 1 and explained in the following.

According to the TAM, an individual's behavioral intention to use a technology (IU) is determined by the perceived ease of use (PEOU) and perceived usefulness (PU) of this technology (DAVIS 1989). PEOU is defined by Davis (1989) as the degree to which an individual perceives using a technology as easy or effortless. PU refers to the extent an individual perceives that a technology enhances his or her job performance. PEOU also affects PU since, the easier a technology is to use for an individual, the higher the perceived usefulness by that same individual, *ceteris paribus* (DAVIS 1989). Borchers and BEWLEY (2015) show that dairy farmers who do not know how to use precision dairy farming technologies, are less likely to be adopters. Thus, if a dairy farmer thinks implementing and using a herd management smartphone app is easy, he or she has a higher IU such an app. Moreover, if a dairy farmer perceives handling a herd management smartphone app as difficult or learning to use it as very time consuming, he or she may come to the conclusion that such an app is not useful. A DST should provide information which is useful for the farmers' work, as otherwise adoption will not take place (ROSE et al. 2016; BONKE et al. 2018). Moreover, the literature provides evidence that adoption of innovative technologies happens if, for instance, producers strive to improve their efficiency and a technology is perceived as useful for that purpose (EL-OSTA und MOREHART 2000). To summarize, if a dairy farmer perceives herd management smartphone apps as useful to obtain information to make better production decisions or to observe animal behavior, he or she is more likely to have a higher IU herd management smartphone apps. The target construct of the TAM is the actual usage behavior, which is influenced by the IU a technology. In contrast to DAVIS (1989), the actual usage behavior is not modelled as a dummy variable, but as an ordinal variable, measuring the frequency of dairy herd management app use. The following hypotheses represent the described relationships:

H1a: The perceived ease of use has a positive effect on the perceived usefulness of herd management smartphone apps.

H1b: The perceived ease of use has a positive effect on the intention to use herd management smartphone apps.

H2: The perceived usefulness has a positive effect on the intention to use of herd management smartphone apps.

Besides the beliefs about the technology, which are captured by the classical TAM framework, farmers' as well as farm characteristics play a crucial role for technology adoption. Therefore, our TAM is extended by several variables which are hypothesized to influence the key constructs PU and PEOU. In the agricultural context, farm size plays an essential role for technology adoption, for instance smartphone adoption (MICHELS et al. 2019). With respect to dairy technology adoption, GARGIULO et al. (2018) provide evidence that larger herd sizes increase the likelihood of adoption of new technologies. LAZARUS et al. (1990) expect that benefits from data collection and evaluation for individual animals are higher for larger herds, since individual animal management becomes more challenging with increasing herd size. This could be facilitated by the use of smartphone apps (HERD 2014; DEBAUCHE et al. 2018). Thus, it is plausible that dairy farmers with larger herd sizes have a higher perceived usefulness of herd management smartphone apps. Hence, we hypothesize the following:

H3: Managing larger herd size has a positive effect on the perceived usefulness of herd management smartphone apps.

EL-OSTA and MOREHART (2000) show that milk yield and technology adoption are positively related. Their findings suggested that producers with better performing herds try new technologies to maintain their production level or to achieve even higher production gains. Hence, it is also plausible that a dairy farmer with a high milk yield may want to maintain or increase his or her high production level and thus perceives the information and functions provided by herd management smartphone apps as more useful. We therefore hypothesize the following:

H4: Increasing milk yield has a positive effect on the perceived usefulness of herd management smartphone apps

One of the major influences on technology adoption discussed in the literature is the age of the farmer (GHADIM and PANNELL 1999). LEWIS (1998) suggests that older farmers have a lower demand for management of information due to their higher farming experience. This implies with respect to our research, that an older dairy farmer may benefit less from the information provided by using herd management smartphone apps since he feels experienced enough to not be dependent on such an app. Furthermore, he or she may have already established other sources of information or DST and therefore does not perceive herd management smartphone apps as useful. Moreover, skills to work with mobile devices are likely to be better among younger adults, which also hold true with respect to younger farmers and their use of computers and smartphones (ROSE et al. 2016). Hence, an older dairy farmer who is less experienced with smartphones or digital technologies may perceive herd management smartphone apps as difficult instruments to use and therefore rate their usefulness lower. All in all, this is indicated by the following hypotheses:

H5a: Increasing age has a negative effect on the perceived usefulness of herd management smartphone apps.

H5b: Increasing age has a negative effect on the perceived ease of use of herd management smartphone apps.

TAYLOR and TODD (1995) suggest that prior experience with information technologies positively influences the adoption of similar technologies in general. Specifically, an individual may have learned the technical skills required to work with a certain technology and is therefore better equipped to handle a similar or more advanced technology (GHADIM and PANNELL 1999). For DST in general, ROSE et al. (2016) reason that farmers who are accustomed to computers and smartphones will be more likely to use new software and apps, as these may not be as difficult to adopt considering their current use of technology. In line with that, BONKE et al. (2018) show those farmers who were aware of the existence of crop protection apps, are more likely to be willing to pay for these apps. Hence, it is plausible that a dairy farmer, who is aware and already informed about herd management smartphone apps, perceives the use as easier than dairy farmers who have no knowledge about such apps. Likewise, it could be expected that dairy farmers who have knowledge about herd management smartphone apps can assess the benefit of using them, i. e. perceived usefulness, better than farmers with no knowledge. This is also expressed by the following hypotheses:

H6a: Knowledge of herd management smartphone apps has a positive effect on the perceived ease of use of herd management smartphone apps.

H6b: Knowledge of herd management apps has a positive effect on the perceived usefulness of herd management smartphone apps.

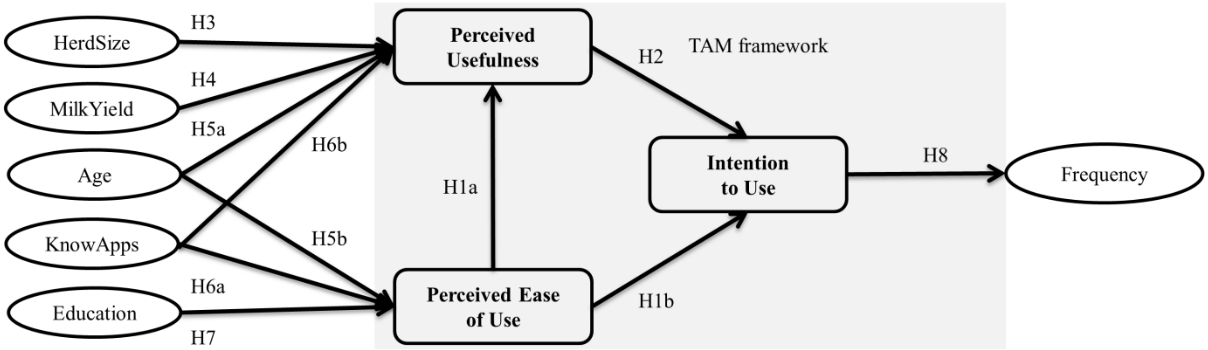
Education is considered to be one of the most important socioeconomic factors in information technology adoption (RIGGINS and DEWAN 2005), since education improves an individual's ability to understand and decode information (NELSON and PHELPS 1966). Effective usage of herd management smartphone apps may require substantial learning. AMPONSAH (1995) argue that for farmers with increasing levels of education, the ability to learn how to use a computer and to make value of the produced information also increases. Therefore, it can be concluded that a higher level of education eases the adoption and use of herd management smartphone apps for dairy farmers. This is displayed by the following hypothesis:

H7: Higher Education has a positive effect on the perceived ease of use of herd management smartphone apps.

The target construct of the TAM is the actual usage behavior, which is influenced by the IU a technology. In contrast to DAVIS (1989), the actual usage behavior is not modelled as a dummy variable, but as an ordinal variable, measuring the frequency of dairy herd management app use. This is described by the following hypothesis:

H8: The intention to use has a positive effect on the frequency of using herd management smartphone apps.

Figure 1: Proposed extended TAM for the adoption herd management smartphone apps



Source: Authors‘ illustration

2.2 Data collection

An online survey addressed to German dairy farmers was conducted from March to May 2018. Dairy farmers were found via social media channels and the Alliance of German Dairy Farmers. The survey was structured as follows: First, dairy farmers were requested to give their evaluation of ten randomized statements which are the basis for the developed TAM for dairy herd management apps. We used five-point Likert scales (1 = fully disagree; 5 = fully agree) for the statements of the TAM. Second, dairy farmers were asked to evaluate the usefulness of several herd management app functions on five-point Likert scales (1 = not useful at all; 5 = very useful). Following BONKE et al. (2018) we chose to ask about functions of an app rather than about specific apps to avoid potential bias, since specific apps might not be known by all respondents. Additionally, this supports the generalizability of our results for dairy sectors and developers outside Germany. Third, farmers were asked to provide information on their smartphone and herd management app use. Specifically, farmers were asked about their herd management app use frequency (1 = never; 2 = less than once a week; 3 = weekly; 4 = more than once a week; 5 = daily; 6 = more than once a day). Multiple answers were not allowed.

2.3 Model Estimation

In order to estimate the previously described TAM (see Figure 1), we used structural equation modeling (SEM), since we wanted to simultaneously estimate the relationship between constructs as well as the relationship between indicators and constructs. Specifically, we applied partial least squares structural equation modeling (PLS-SEM), because this approach is less restrictive concerning the structure of the data than covariance-based SEM which requires normally distributed data. Furthermore, PLS-SEM allows the use of constructs with only one or two items (HAIR et al. 2011). PLS-SEM aims to maximize the explained variance of the endogenous variables. The model consists of two parts: the outer (relationship between indicator and construct) and the inner model (causal relationship between constructs). All indicators in the TAM are reflective indicators (VENKATESH and BALA 2008). We therefore applied IU, PEOU and PU as reflective constructs. Single items are always defined as reflective variables. Exogenous variable like dairy farmers’ education are therefore applied as reflective variables (HAIR et al. 2017). PLS-SEM models were evaluated in two steps: Firstly, the outer model is analyzed and then the inner model is assessed. The endogenous variable of the PLS-SEM is the IU. To avoid biased standard errors, the effect of IU on the Frequency is estimated using an ordinal logit model.

2.4 Results

2.4.1 Descriptive Results

The descriptive statistics are given in Table 1. As can be observed, the dairy farmers in our sample are comparatively younger and more educated than the German average. However, as pointed out by BONKE et al. (2018) with respect to the future development of DST, such as smartphones and associated apps, it is worthwhile to focus on adoption by younger farmers, since they are most likely to be the long time users (ROSE et al. 2016).

Table 1. Descriptive statistics (n=280)

Variable	Description	Mean	SD	Min	Max	German Average[1)]
Age	Farmers' age in years	40.17	11.54	21	66	53
ArableLand	Arable land in hectares	183.90	410.06	0	2,900	60.50
Education	1 if the farmer has a university degree; 0 otherwise	0.22	-	0	1	0.12
Frequency	Frequency of herd management app use, 1 = never; 2 = less than once a week; 3 = weekly; 4 = more than once a week; 5 = daily; 6 = more than once a day	3.39	2.14	1	6	n. a.
Gender[2)]	1 if the farmer is male; 0 otherwise	0.78	-	0	1	0.90
Grassland	Grassland in hectares	85.35	148.45	0	1,700	34.70
HerdSize	Number of dairy cows	169.13	190.39	9	1,450	63
HMApp	1 if the farmer uses a herd management app; 0 otherwise	0.61	-	0	1	n. a.
HMPC	1 if the farmer uses a herd management PC software; 0 otherwise	0.81	-	0	1	n. a.
KnowApps	1 if the farmer knows apps that can be used for herd management; 0 otherwise	0.75	-	0	1	n. a.
MilkSys	Milking system used on the farm					
	Milking parlor	0.66	-	0	1	n. a.
	Rotary milking parlor	0.10	-	0	1	n. a.
	Automatic milking system	0.23	-	0	1	n. a.
MilkYield	Milk yield in kg per cow and year	9,049	1,368	5,000	12,500	7,746
PastureAcc	1 if the cows have pasture access; 0 otherwise	0.47	-	0	1	n. a.
Smartphone	1 if the farmer has a smartphone; 0 otherwise	0.93	-	0	1	0.58

1) Sources: Kleffmann Group (2016), DBV (2018)

A smartphone is owned by 93 % of the dairy farmers, which lies above the German average of 58 %. 75 % of the dairy farmers know about smartphone apps, which can be used for herd management purposes. A total of 61% of the dairy farmers already use a herd management smartphone app. Hence, not all dairy farmers who are aware of herd management smartphone apps also use them. A total of 39 % of the dairy farmers never use a herd management app. On the same level, 38 % of the dairy farmers in our sample use a herd management app at least once a day (8.21 % daily; 29.64 % more than once a day). Almost 20 % of the dairy farmers use a herd management app at least weakly (6.07 % weekly; 13.93 % more than once a week). Only less than 4 % use a herd management less than once a week.

Farmers were asked to rate the usefulness of the presented herd management app functions to support their herd management. To check for differences in the usefulness scores for several topics between users and non-users, we applied a Mann-Whitney *U*-test. The usefulness scores in Table 2 for data gathering, reproduction management and animal health functions were statistically significantly greater for dairy farmers already using a herd management app compared to those that were not. Furthermore, these functions may benefit the most from the smartphone mobility with respect to dairy farmers' perceived usefulness since the information can be entered in real time and retrieved from anywhere at any time. No statistically significant difference was found for functions with respect to feed management and milking control. Moreover, these functions received the lowest usefulness scores. App functions with respect to feed management may not benefit from the mobile character of smartphones. Additionally, feed ratio calculation and feeding may already be automated.

Table 2. Usefulness scores of several herd management app functions comparing farmers using and not using a herd management smartphone app (n=280)

Function	Mean usefulness scores[1)]			
	Using[2)]	Not Using[2)]	Difference	Test
Reproduction management (e.g. bull selection, timing of drying off cows)	4.26	3.70	0.56	Mann-Whitney *U****
Animal health (e.g. animal positioning and monitoring of lying and feeding behavior)	4.04	3.66	0.38	Mann-Whitney *U***
Data gathering (e.g. cow management, performance recording, time and labor management)	3.86	3.50	0.36	Mann-Whitney *U**
Milking control (e.g. control of tanks, control of milking technique)	3.70	3.56	0.14	Mann-Whitney *U*
Feed management (e.g. calculation of feed ratios)	3.07	2.92	0.15	Mann-Whitney *U*

[1)] Likert scale 1 = not useful at all; 5 = very useful.
[2)] Specification according to the Dummy-Variable HMApp = 1 (n=172) and HMApp = 0 (n=108).
$^{*}P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$

2.4.2 Evaluation of the Technology Acceptance Model

For the assessment of the outer model of the estimated TAM, indicator reliability, internal consistency reliability, convergent validity, and discriminant validity are tested. Discriminant validity refers to the extent to which the constructs are separable from other constructs. In our study, discriminant validity is established by the Heterotrait-Montotrait (HTMT) criterion. All values for our outer model fit the cut-off levels as shown in Tables 3 and 4. Therefore, the outer model can be described as valid (HAIR et al. 2017). Our model explains 63% of the variance in the IU herd management apps. The value can be described as substantial (COHEN 1988). Furthermore, explained variance in PEOU and PU amount to 39% and 18%, which can be classified as substantial and moderate, respectively (COHEN 1988). Since no assumption about the distribution of the data is needed for PLS-SEM, results for hypotheses testing of the path coefficients of the inner model are derived from a re-sample bootstrapping procedure. According to HAIR et al. (2014) at least 5,000 subsamples should be applied to generate t-values to allow for hypothesis testing. The results for the inner model and ordinal logit model are shown in Table 5.

Table 3. Evaluation of the outer model (n=280)[1)]

Construct	Indicator	Loadings	Cronbach's α	Composite reliability ρ_c	Dijkstra-Henseler's ρ_a	AVE
IU			0.912	0.958	0.912	0.919
	iu1	0.958***				
	iu2	0.959***				
PEOU			0.875	0.912	0.896	0.723
	peou1	0.858***				
	peou2	0.891***				
	peou3	0.833***				
	peou4	0.817***				
PU			0.853	0.901	0.867	0.694
	pu1	0.858***				
	pu2	0.796***				
	pu3	0.888***				
	pu4	0.788***				

[1)] Cut-off level for standardized indicator loadings > 0.7; Cronbach's α > 0.7; Composite reliability ρ_c > 0.7; Dijkstra-Henseler's ρ_a > 0.7; AVE > 0.5. IU = Intention to use; PEOU = Perceived ease of use; PU = Perceived usefulness; AVE = Average variance extracted
$^{*}P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$

Table 4. Discriminant validity: Heterotrait-Monotrait criterion (n=280)[1)2)]

	Education	Herd Size	IU	MilkYield	PEOU	PU	Age
Education							
Herd Size	0.216						
IU	0.095	0.050					
MilkYield	0.131	0.264	0.249				
PEOU	0.200	0.082	0.720	0.100			
PU	0.062	0.039	**0.841**	0.220	0.657		
Age	0.073	0.016	0.071	0.006	0.136	0.076	
KnowApps	0.114	0.042	0.438	0.019	0.417	0.349	0.105

Highest value is given in bold.
[1)] The cut-off level for the Heterotrait-Monotrait criterion is < 0.9.
[2)] IU = Intention to use; PEOU = Perceived ease of use; PU = Perceived usefulness

Table 5. Inner model results and hypothesis testing (n=280)[1)]

Partial Least Squares Structural Equation Modelling

H_0		Path coefficients	t-statistic (Bootstrap results)[2)]	Supported H_0
PEOU → PU	H1a	0.548***	12.660	Supported
PEOU → IU	H1b	0.336***	5.504	Supported
PU → IU	H2	0.547***	10.303	Supported
HerdSize → PU	H3	-0.070	1.390	Not supported
MilkYield → PU	H4	0.169***	3.380	Supported
Age → PU	H5a	0.001	0.145	Not supported
Age → PEOU	H5b	-0.074	1.417	Not supported
KnowApps → PEOU	H6a	0.381***	7.019	Supported
KnowApps→PU	H6b	0.107**	2.158	Supported
Education → PEOU	H7	0.135**	2.583	Supported

Ordered Logit Model

H_0		Odds ratio	Std. Error	Supported H_0
IU→Frequency	H8	3.82***	0.571	Supported

[1)] PU = Perceived Usefulness; PEOU = Perceived Ease of Use; IU = Intention to use
[2)] 5,000 subsamples
[3)] Nagelkerke R^2 = 0.335, LR chi^2 (2) = 107.26***, Log likelihood = -365.49, Brant chi^2 = 7.79 (not statistically significant)
**P* < 0.05, ***P* < 0.01, ****P* < 0.001

A path coefficient can be interpreted as standardized beta coefficient (HAIR et al. 2017). The path coefficient for PEOU→PU has the expected positive sign and is statistically significant different from zero. Thus, **H1a** is supported by our model. Therefore, if a dairy farmer perceives usage of herd management smartphone apps as easy, he or she perceives such an app as more useful. Dairy farmers who perceive handling an app as easy may benefit more from the various functions. Furthermore, our results support **H1b**, since the path coefficient for PEOU→IU is statistically significant different from zero and has the expected positive sign. Thus, a perceived effortless handling of a herd management smartphone app increases a dairy farmer's intention to use such an app. **H2** analyses the effect of PU on IU. The path coefficient for PU→IU is statistically significant different from zero and has the expected positive sign. It can be concluded that if a dairy farmer perceives the function provided by herd management smartphone apps as useful for his or her operational activities, he or she has a higher intention to use such apps. The path coefficient for HerdSize→PU does not have the expected sign and is not statistically significant, therefore **H3** is not supported. The missing statistical significance of the effect can be explained by the fact that for smaller herd sizes, observing and collecting animal individual data is important for an effective herd management as well. The results imply that herd management smartphone apps are also of interest for small producers to facilitate for instance animal observation. Nevertheless, a positive effect was expected, since larger farmers are more likely to be the adopter of smartphones (MICHELS et al., 2019) or sensor technologies (GARGIULO et al. 2018) which could be combined with smartphone apps. Thus, it would have been plausible that dairy farmers from larger farms may gain higher benefits from these apps and perceive them as more useful. However, considering the fact that larger farmers can bear higher investment cost due to economies of scale, this is also an important result, as apps functioning without sensor technology and smartphones can be less expensive and therefore more affordable for smaller producers. **H4** addresses the effect of milk yield on PU. The path coefficient for MilkYield→PU has the expected positive sign and is statistically significant different from zero. A high milk yield implies that a farmer has already established a well-functioning herd management system. With the help of herd management smartphone apps, he or she can adjust more easily to small changes and therefore maintain or even increase the high milk yield. Whereas inferior milk yields imply that comprehensive changes in the herd management should be taken into account which cannot solely be solved and assisted by using herd management smartphone apps. The path coefficient for Age→PU does not have the expected sign and is not statistically significant indicating that farmers' age has no statistically significant effect on perceived usefulness. Hence, **H5a** cannot be supported. Although older dairy farmers may have more experience with respect to herd management, using an app can still provide information faster and in a comprehensive manner, thus older dairy farmers also perceive these functions as useful. In particular, the observation of moving and lying behavior could be facilitated with apps and can consequently facilitate animal observation for dairy farmers of all ages. With respect to **H5b**, the path coefficient for Age→PEOU has the expected sign but is not statistically significant. Since younger farmers are more experienced with digital technologies (ROSE et al. 2016), a statistically significant effect was expected. However, as shown by the descriptive statistics in Table 1, most of the dairy farmers in our sample have a smartphone and can thus be described as being familiar, at least on a basic level, with smartphone technology. This could explain why the age of the farmers does not have a statistically significant effect.

H6a and **H6b** analyse the effect of the knowledge of herd management apps on PEOU and PU. The path coefficients for KnowApps→PEOU and KnowApps→PU have the expected positive signs and are statistically significant different from zero. Since knowledge about specific herd management apps implies that farmers can better evaluate the function of an app and therefore perceive the use of such an app as easier and also better asses their benefit (BONKE et al. 2018), this result is reasonable. Thus, awareness of herd management smartphones could increase the PU and ultimately adoption behavior of dairy farmers. **H7** describes the effect of dairy farmers' education on the PEOU. The path coefficient for Education→PEOU has the expected positive sign and is statistically significant different from zero. A higher level of education therefore facilitates the use and adoption of herd management smartphone apps, since education enables a farmer to process information regarding new technologies more easily (POOLSAWAS and NAPASINTUWONG 2013). Furthermore, it can be expected that dairy farmers, who hold a university degree may have more experience with digital technologies, like computers and internet, while being at university and thus perceive handling herd management apps as more easy. Additionally, BRAMLEY and OUZMAN (2018) showed that digital literacy could facilitate adoption of precision agriculture technologies. With respect to PEOU, BORGHI et al. (2016) reasoned that precision agricultural technologies should be kept simple in use, which also holds true for the development and use of herd management smartphone apps according to our results. Lastly, our model also supports **H8**, since the odds ratio for IU→Frequency are greater than one and statistically significant different from zero. Hence, the IU has a positive effect on the usage behavior. Thus, all hypotheses of the original TAM could be supported, which verifies one of our research goals. The TAM can be applied to herd management smartphone app adoption in dairy farming.

3 Conclusions

This study provides a greater understanding of the adoption and use of herd management smartphone apps by German dairy farmers. We also assessed which herd management app functions are perceived as most useful. More than 38% of the dairy farmers use herd management smartphone apps on a daily basis, while 39% do not use any herd management smartphone app. Animal health observation, reproduction management and data gathering functions are perceived as very useful by German dairy farmers. Developers and providers should focus on these functions for future development. Since not all dairy farmers who are aware of herd management smartphone apps are also users of such apps, there is large potential for increasing the adoption and usage of smartphones and related apps in dairy herd management through effective marketing and advertising for which the results of this study can be used.

This study shows that the assumptions of the TAM hold true for the intention to adopt and the actual use of herd management smartphone apps in dairy farming. Key attitudinal beliefs about the perceived ease of use and the perceived usefulness are major determinants of the intention to use, which in turn strongly influences the actual use of herd management smartphone apps. Consequently, benefits of usage should be clearly visible for farmers in order to promote more widespread adoption. In line with that, handling of an app and provision of information should be kept as simple as possible to make herd management smartphone apps attractive for farmers regardless of educational background and previous knowledge. The results also imply that herd management smartphone apps are perceived as useful by dairy farmers of all sizes which should also be considered by developers and providers. Our study also has some limitations: We did not ask for reasons why farmers do not use herd management smartphone apps, which could have been interesting for developers and providers, since not all dairy farmers in our sample who know about herd management apps also use them. Furthermore, evaluation of willingness-to-pay for herd management smartphone apps could be an interesting research topic, as the assessment of the financial value of a DST is an important part of the development process besides the assessment of the usefulness.

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