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ORIGINAL ARTICLE

Determinants of Small-Scale Farmers' Intention to Use Smartphones for Generating Agricultural Knowledge in Developing Countries: Evidence from Rural India

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Abstract
Access to and usage of smartphones for agricultural purposes amongst small-scale farmers in rural areas of developing countries is still limited. Smartphones may provide an opportunity to develop farmers' capacities with specific applications offering fast access to continually updated and reliable information. This study develops a framework to investigate the cognitive and affective behavioural drivers of smallholder farmers´ intention to use a smartphone in a developing country context. For this, survey data was collected from 664 randomly selected small-scale farmers in Bihar State, India in 2016. The analysis included a partial least square estimation of the behavioural model. The results confirm positive influences on the intention to use a smartphone for agricultural purposes through subjective norms, attitude, self-control, as well as positive and negative anticipated emotions. There is no evidence that negative anticipated emotions related to failure outweighed other factors. These results extend the academic literature with new conceptual insights and provide application-oriented implications for stakeholders, such as NGOs, extension services and research institutes.

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Résumé
L'accès aux smartphones et leur utilisation à des fins agricoles par les petits agriculteurs des zones rurales des pays en développement restent limités. Les smartphones présentent une occasion de renforcer les capacités des agriculteurs grâce à des applications spécifiques qui offrent un accès rapide à des informations mises à jour en continu et fiables. Cette étude développe un cadre pour étudier les moteurs comportementaux cognitifs et affectifs qui déterminent l'intention d'utiliser un smartphone de la part des petits exploitants agricoles dans un pays en développement. Pour cela, des données d'enquête ont été collectées auprès de 664 petits agriculteurs sélectionnés au hasard dans l'État du Bihar, en Inde en 2016. L'analyse comprenait une estimation partielle des moindres carrés du modèle comportemental. Les résultats confirment les influences positives sur l'intention d'utiliser un smartphone à des fins agricoles des normes subjectives, de l'attitude, de la maîtrise de soi, ainsi que des émotions anticipées positives et négatives. Rien ne prouve que les émotions négatives anticipées liées à l'échec l'emportent sur d'autres facteurs. Ces résultats viennent s'ajouter à la littérature académique en offrant de nouvelles perspectives conceptuelles, et ont des implications relatives aux applications pour les parties prenantes, que ce soit des ONG, des services de proximité et des instituts de recherche.

Introduction

Agricultural production is complex, and farmers need to make proper and timely decisions on a range of several agricultural subjects at different stages of the production cycle. To this end, external information sources may provide farmers with input to help with the best time for seeding, to improve market access or to adopt more efficient technologies (Aker 2011; Mittal et al. 2010). In this regard, it is not only the pure access to information but also the generation of knowledge through combining, reflecting and concluding on information sought, that should enhance farmers' capacities (Aker et al. 2016). Smallholder farmers in the rural areas of developing countries are still especially disadvantaged with regard to capacities involving modern sustainable farming practices. In such a developing country context, the most common measures with which to disseminate knowledge over the past decades have been extension services such as Farmer-Field-Schools or Self-Help-Groups based on frontal teaching methods to farmers or with direct interaction with experts through a participatory and demand-driven approach (Phillips et al. 2014). The necessity of personal presence and the resulting inequalities of access have been criticised as inhibiting such measures' efficiency (Phillips et al. 2014).

Information and Communication Technology (ICT) provide potential for developing farmers' management capacity. Additionally, ICT can also be catalyst to improve the effectiveness of the agricultural extension system (Glendenning and Ficarelli

2012). Existing studies on ICT usage in developing countries' agricultural sectors have either focused on socio-economic adoption drivers (e.g. Aleke et al. 2011), on cognitive usage drivers (Verma and Sinha 2016), or on usage-related performance effects (e.g. Aker 2011; Sekabira and Qaim 2017). Recent research has suggested that smartphones may provide an opportunity to further develop farmers' capacities through specific applications offering fast access to continually updated and reliable information (Aker 2011; Aker et al. 2016). However, the access and usage of smartphones for agricultural purposes among small-scale farmers in rural areas of developing countries is still limited, even though this type of phone is becoming more widespread. The recent literature on this topic explains the phenomenon with emphasis on restrictions in basic and work-specific digital literacy, an argument which is gaining relative importance compared to the individual lack of financial resources to pay for the technique and the general unavailability of IT infrastructure and internet coverage (World Bank 2016a; Deichmann et al. 2016; Zhang 2016). Consequently, farmers who own a smartphone, but do not use it in a work-related manner, may still perceive similar usage-barriers as those farmers who do not own a smartphone yet. During smartphone usage decisions in general, digital literacy manifests itself in complex behavioural processes consisting of cognitive and affective drivers. Even though, the so called "emotional lift" has been detected as an important affect in other smartphone usage cases (Lee and Shin 2016), to the best of our knowledge, no previous study has examined the drivers of farmers' smartphone usage for agricultural purposes by taking the affect into account. Based on a conceptual model which integrates Perugini's and Bagozzi's (2001) goal-based behavioural model with the model of technology acceptance by Cheon et al. (2012) and Venkatesh and Davis (2000), the objective of the present study is to develop and empirically test a comprehensive behavioural model for identifying and quantifying the cognitive and affective drivers of smallholder farmers´ intention to use a smartphone in developing countries. For this purpose, primary data from 664 small-scale farmers was collected in Bihar State, India, in 2016. The results of this study may provide the foundation for concrete smartphone implementation strategies in the agricultural production sectors of developing countries.

The Indian state of Bihar has a high population density of more than 100 million inhabitants, of which 34% live below the poverty line—1.90 USD per day. A large proportion of the population (89%) lives in rural areas with geographically diverse terrain and mostly in scattered villages (Census Organisation of India 2015; Chauhan 2010; World Bank 2016a). Correspondingly, 62% of the population works in the agricultural sector. As in many other developing countries, agriculture in Bihar shows low crop productivity, lack of water management, low investment rates, and weak infrastructure with regards to transport and marketing (Rodgers et al. 2013; World Bank 2005). Such circumstances are addressed by NGOs such as' Farms and Farmers Foundation' (FnF) and 'Preservation and Proliferation of Rural Resources and Nature' (PRAN) through capacity development activities (Census Organization of India 2015). However, NGO's reach to smallholder farmers is impeded by limited information and communication technology (ICT) coverage. In 2011 mobile phone coverage still provided for only 52% of the Biharian population (Census

Organisation of India 2015), over 10% less compared to the whole Indian population in 2010 (Jain et al. 2015), but 16% more compared to the Indian farmers/agricultural labour force in 2010/2011 (Cole and Fernando 2012). The share of mobile phone owners over the whole of India using smartphones increased from 21% in 2014 up to 33% in 2017 (Statista 2018). Furthermore, data from the Telecom Regulatory Authority of India (2017) give evidence that the number of wireless subscribers in rural India has been steadily increasing since 2012 and almost reached the 500 million mark in 2017.

The Role of Smartphones for Agricultural Capacity Development

Modern ICTs have enabled the increasing use of mobile phones for capacity development purposes in developing countries' agricultural sectors as they have done elsewhere. The distance-eliminating character of this technology is especially recognized as one of its major advantages. Consequently, Short Message Service (SMS) is nowadays still the most applied digital technology used in agricultural extension projects (Aker 2011; Deichmann et al. 2016) even though mobile phone successor technology, smartphones and corresponding internet applications, have been on the advance over recent years. Smartphones, with their advances in size, hardware and applications, provide additional possibilities to measure a variety of data such as the lightening level, GPS coordinates or humidity. Furthermore, they are able to capture, store and transfer information in different formats such as text, pictures, audio, and video very rapidly.

Smartphones are considered to offer potential access to information, generational knowledge, extension services, market linkages, distribution networks, financial resources, new technologies and other inputs (Aker 2011; Deichmann et al. 2016). Such access has already been identified in predecessor ICTs' usage with numerous studies on various cases all over the world looking at increasing household/farm marketing performance (e.g. Aker 2011; Beheraa et al. 2015; Sekabira and Qaim 2017), production performance (e.g. Aker 2011; Cole and Fernando 2012) or both (e.g. Ali and Kumar 2011; Deichmann et al. 2016; Rao 2007). Consequently, smartphone usage can be expected to improve income generation and thus poverty reduction in developing countries' agricultural sectors. Simultaneously, smartphone technology can allow stakeholders, such as NGOs or financial institutions, to have a targeted design and to share customised, more detailed information at lower cost. Smartphones represent an upcoming tool which can generate agricultural knowledge through capacity development measures more efficiently than frontal teaching methods or even other ICTs can (e.g. Sinha and Sing 2014).

Despite this potential and increasing access to the technology, adoption and usage rates among farmers in developing and emerging economies are still relatively low. Such disparities have already been observed for predecessor ICTs and motivated researchers to take account of psychological usage drivers—conceptually as well as empirically. In their qualitative argumentation, Kameswari et al. (2011) include psycho-economic factors by highlighting "socio-cultural context" factors. Trust within farmers' business networks, combined with favourable production conditions are regarded as crucial for ICT usage in general and information search in particular, within the Indian agricultural sector. The study by Venkatesh and Sykes (2013) extended conceptual ideas on the role of social networks for the successful implementation of digital divide initiatives in rural India. They developed and tested a framework based on social network theory in comparison to traditional theory of planned behaviour (TBP) and technology acceptance model (TAM) applications. These are well-established in academic literature on non-agricultural cases. Here farmers' PC usage behaviour was based on shared use of PCs provided in an internet kiosk and under supervision. For this type of intermediated ICT use, the social network framework's greater explanatory power was observed, although also recognising that for other types of use, different models have to be developed. In line with this finding, Verma and Sinha (2016) successfully applied TAM to analyse mobile-based agricultural extension service under independent individual usage in India. Nevertheless, further development of such individual-centric approaches beyond purely cognitive considerations remains neglected in the academic literature on individual ICT usage among farmers in developing countries.

Conceptual Framework

The conceptual framework in Fig. 1 puts forward a combination of the goal-based behavioral model (MGB) (Perugini and Bagozzi 2001) based on the Theory of Planned Behavior (TPB) (Ajzen 1991), and the Technology Acceptance Model (TAM) and its further advances based on Cheon et al. (2012) and Venkatesh and Davis (2000). The TAM part of the model addresses the case-specific character of

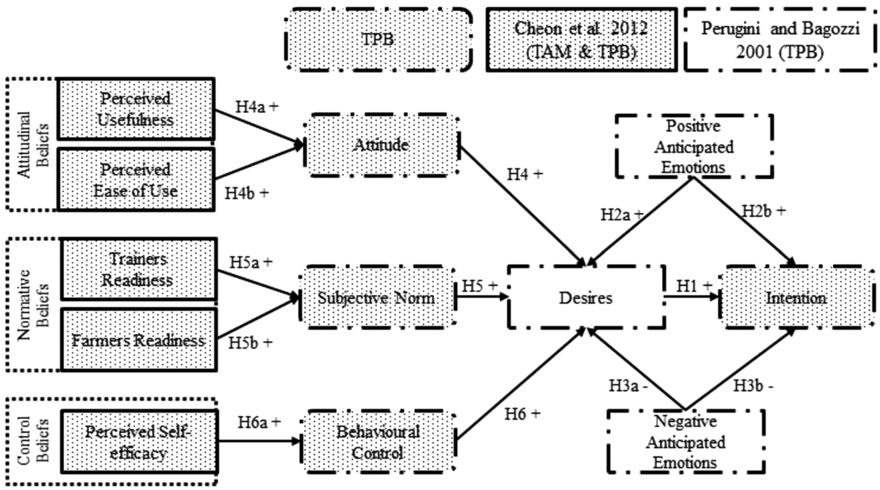

Fig. 1 Smartphone research model with hypotheses. Source: authors own graphic based on Cheon et al. (2012); Perugini and Bagozzi (2001)

the action, namely the acceptance of a new technology as part of the intention to use it for generating agricultural knowledge. The MGB broadened the TPB by introducing desires as the most proximal determinant of intention, since the TPB is silent on how intentions become energized (Perugini and Bagozzi 2001). As the majority of Biharian farmers did not own a smartphone in 2016, actual smartphone usage behaviour for capacity development activities was not measurable. Due to these circumstances, the main outcome variable at that time of the survey was intention.

TPB and relative approaches, especially TAM and TAM 2, have been successfully applied in earlier studies to predict behaviour regarding technology, IT-acceptance, ICT-usage and intention towards agricultural practices among others (e.g. Cheon et al. 2012; Krone et al. 2016; Venkatesh and Sykes 2013; Verma and Sinha 2016; Zeweld et al. 2017). The TPB defines behavioural control, attitude and subjective norm as key-determinants of the behavioural intention. Thereby, behavioural control describes the perceived level of ease an individual ascribes to the conduction of a certain action. This self-evaluation exceeds personal opportunities and resources such as education and income. In the specific context of smartphone usage among small-scale farmers in developing countries, behavioural control reflects the perception of control over the functionality of the smartphone and its applications. Next, attitude denotes the degree of overall favourability assigned to the particular technology from an individual's perspective. In contrast, subjective norm acknowledges the role of social pressure from the personal network related to the performance or non-performance of a particular action. In this study, it can be described as the individual farmer's perception of the opinion on smartphone usage for capacity development prevailing among other individuals' in his or her social and professional network (Ajzen 1991). This study then hypothesises that the intention to use the smartphone technology is positively related to behavioural control (**H6+**), attitude (**H4+**) and subjective norm (**H5+**), however, not directly.

In relation to the TPB, desire can be described as a motivational impetus for the behavioural intention resulting from personal awareness and acceptance of the desire to act (Davis 1984). It is therefore hypothesised that desires reflect the transformation of attitude, subjective norms and behavioural control into a motivation to act **(H1+)** (Leone et al. 1999; Perugini and Bagozzi 2001)**.** Furthermore, Perugini and Bagozzi (2001) broadened the TPB by acknowledging the existence of personal goals associated with certain behaviour. In the case of smartphone usage for generating agricultural knowledge, such goals could be; innovativeness, technological progress and improvements in economic and farming performance (Deichmann et al. 2016). Anticipated emotions are meant to explain goal achievements (positive anticipated emotions) or goal failures (negative anticipated emotions) in the MGB (Perugini and Bagozzi 2001). In this context, such anticipated emotions are described as prefactural appraisals since they capture decision makers' imagined consequences before taking real action (Gleicher et al. 1995) and create the so called "emotional lift" (Lee and Shin 2016). Following Perugini and Bagozzi (2001), it is assumed that positive anticipated emotions and negative anticipated emotions are included as direct predictors of desire in our framework (**H2a+; H3a−**). Different to the MGB, the influence of these two variables is also tested on the construct intention (**H2b+; H3b−**) to take into account the bounded rationality of the affect (Zhang and Li 2005).

In accordance with the TAM 2-model developed by Venkatesh and Davis (2000) and the subsequent conceptualization by Cheon et al. (2012), the main TPB-determinants to intention; attitude, subjective norm and behavioural control are assumed to be influenced by three different types of salient beliefs: attitudinal beliefs, normative beliefs and control beliefs (Ajzen 1991).

Attitudinal beliefs comprise perceived usefulness and perceived ease of use. Perceived usefulness reflects individual user-beliefs regarding the advantageousness of a technology for own job performance and consequent life-quality (Verma and Sinha 2016). In several studies regarding ICT innovations usefulness is a proven and important motivator for acceptance (e.g. Liu et al. 2010). Perceived ease of use describes users' beliefs regarding the expected individual time- and strain-effort connected to the technology usage, e.g. for learning the functionality of a smartphone (Venkatesh and Davis 2000). These two attitudinal beliefs (**H4a+; H4b+**) are hypothesised to determine attitude.

Normative beliefs represent the individuals' perception of beliefs persisting among important actors in their social and professional network (Ajzen 1991; Cheon et al. 2012). As suggested by Cheon et al. (2012), the present study differentiates between the readiness of trainers and other farmers, both considered the most important actors in the process of agricultural knowledge generation. Since farmers include the beliefs they assimilate from trainers and other farmers' in their own belief structure, the two latent variables of trainer readiness and farmer readiness are hypothesised to influence the behavioural control positively (**H5a+; H5b+**) (Cheon et al. 2012; Venkatesh and Davis 2000).

Control beliefs describe an individuals' self-confidence towards behaviour. Thus, perceived self-efficacy, (Ajzen 1991, 2002; Cheon et al. 2012) captures the beliefs of individuals about their own motivation and ability to behave in a particular manner, such as using a smartphone for agricultural purposes. Furthermore, learning autonomy is expected to be relevant for smartphone usage for agricultural purposes, since its adoption requires a comparatively high degree of self-motivation and self-discipline as a downside to the greater flexibility and mobility it provides (Cheon et al. 2012). Hence, it is hypothesised that perceived self-efficacy (**H6a+**) as well as learning autonomy (**H6b+)** has a positive effect on behavioural control.

Methods and Data

The study is based on a survey questionnaire that was developed following a literature review, with a specific focus on technology acceptance and usage. Participant response bias is a common issue in primary survey data, especially whenever societal differences and differences in origin exist between researcher and respondents. Even if such bias can be reduced to a minimum, as in this study, it can never be fully avoided. This has to be taken into consideration during the further utilization of results (Dell et al. 2012). The measures used were tested in six focus group discussions each with on average 25 farmers during the pre-field visit. Before a pre-testing of the questionnaire was undertaken, all interviewers participated in an intensive survey training lasting four days. The interviews were conducted by natives/locals in the absence of the foreign researcher. The questionnaire included 16 sections, most of which were measured on a 5-point Likert scale format (from 1 = strongly disagree to 5 = strongly agree). Alternative response options from 1 = not at all to 5 = extremely, were provided solely for statements capturing positive and negative anticipated emotions. Table 2 (Appendix) presents the measurement indicators. The questionnaire first presented an info-graphic overview so as to provide a baseline of background information on smartphone usage for agricultural purposes.

From April to July 2016 a total of 664 small-scale farmers, who generate their main income from agricultural activities, were recruited to participate using a stratified random sampling strategy to achieve two relatively equal groups. Stratification was thereby related to cooperation with local NGOs involved in agricultural extension activities, such as FnF and PRAN. The interviews had an average duration of 77 min and were carried out face-to-face by eight trained enumerators with the help of tablets using 'Sawtooth Software'.

Table 1 Demographic data (respondent and household; *N* = 664)

Variable (Respondent)	Freq	Percent	Mean	SD	Min	Max
Age in years			43.06	12.61	13	90
Share of female farmers	214	32.0				
Female household head	49	7.4				
Male household head	329	49.6				
Able to read	490	74.0				
Level of education						
No degree	224	33.7				
Primary School	187	28.2				
Secondary School	179	27.0				
Graduate	58	8.7				
Post-Graduate	16	2.4				
Owner of a mobile phone	492	74.0				
Owner of a smartphone	99	15.0				
Variable (Household)						
Number of household members			6.06	2.49	1	15
Access to electricity	613	92.0				
Access to internet	30	5.0				
Access to radio	83	12.5				
Access to newspaper	89	13.0				
Access to television	217	33.0				
Total own land (acre)			1.76	3.38	0	42.8
Total cultivated land (acre)			1.84	3.39	0	41.4

Source authors own data and calculations

The characteristics of the sample are described in Table 1. The final sample consisted of 68% male and 32% female respondents with an average age of 43 years and a literacy rate of 74%. The share of females in the sample is below the national average of ca. 48% reported in the year 2011 but the majority of the farmland in India is owned by males. In this sample, 74% own a mobile phone and 15% own a smartphone, giving evidence of an increasing penetration of mobile devices in India in recent years. However, none of the farmers owning a smartphone use it for agricultural purposes, including capacity development as the focus group discussions clarified. In this regard, actual usage behaviour could not be included as the final outcome variable of the model. Lack of actual behavioural action hinders any drawing of conclusions on the potential existence of an intention-behaviour gap.

The farmers cultivate 1.8 acres (0.7 ha) on average. Out of all respondents, 30% are PRAN-members, 15% are members of FnF and nine% are members of other governmental or non-governmental organisations such as Jeevika or 'Krishi Vigyan Kendra' (KVK).

The variance-based Partial Least Square (PLS) method was used to analyse the pooled data. The PLS approach is appropriate to test explorative models with complex relations between latent constructs (Chin 1998; Hair et al. 2017; Henseler et al. 2016) despite existing criticism for inconsistencies and biases in estimates (Henseler et al. 2014). The statistical analysis was done with the programme Smart-PLS 3. In addition to a pooled PLS-estimation, a Multi-Group-Analysis according to the stratification criterion was conducted in order to test for a potential bias of outcomes (Sarstedt et al. 2011). During the PLS-estimations, the testing of the measurement model was conducted regarding reliability (indicator reliability and composite reliability) and validity (convergent validity and discriminant validity) criteria, as well as multicollinearity before the hypotheses were tested based on R-square-values, path-coefficients and their significance-levels (Balderjahn et al. 2013; Fornell and Larcker 1981).

Reliability of the indicators is given if all items in the model show factor loadings above the threshold of 0.7 (Henseler et al. 2016) internal consistency if the composite reliability value exceeds 0.7 (Fornell and Larcker 1981) and convergent validity if the Average Variance Extracted (AVE) is greater than 0.5 (Bagozzi and Yi 1988). Discriminant validity is firstly checked by cross-loadings, whereby all items need to have a higher correlation with their assigned factor than with other factors (Henseler et al. 2016). Secondly discriminant validity is tested using the Fornell-Larcker criterion. The criterion is fulfilled if the square root of each construct´s AVE is greater than the correlation with other constructs (Hair et al. 2017). Multicollinearity is checked with the VIF (Variance Inflation Factor). This factor should be smaller than five (Henseler et al. 2016). The explanatory power is evaluated according to the power primer ($R^2=0.1$: small; $R^2=0.3$: middle; $R^2=0.5$: large) developed by Cohen (1992).

PLS-estimation

The parameters for the quality criteria shown in Tables 2, 3, and 4 (Appendix) proof the reliability and validity of the model estimated with the pooled data set. The Multi-Group-Analysis indicates that a bias of results from sample stratification can be rejected since no significant differences between the two strata are found. Figure 2 shows the R-square-values, path-coefficients and their significance-levels of the PLS-estimations. The R-squares range from 0.374 to 0.633 and can, thus, be interpreted as middle to large. The intention construct shows an R-square value of 0.633.

The TPB key-determinants attitude (0.340***; **H4**+), subjective norms (0.217***; **H5**+), and behavioural control (0.164***; **H6**+) have a highly significant influence on desires. Thereby, especially attitudes, show a greater influence than perceived social pressures from farmers' individual networks and their self-evaluation regarding own opportunities to appropriately maintain the smartphone (Venkatesh and Sykes 2013).

Desires are strong and highly significant in influencing intentions (*b*-value = 0.684***; **H1+),** which supports the finding by Perugini and Bagozzi (2001). However, the results for the two emotional constructs are not in accordance with the finding by Perugini and Bagozzi (2001). Positive anticipated emotions have no significant influence on desires **(**– 0.021; **H2a–)** but a strong as well as highly significant influence on intentions (0.251***; **H2b+)**. Reversely, negative anticipated emotions have a relatively low and significant influence on desires **(**0.073**; **H3a+)** but no significant influence on intention **(**– 0.002; **H3b–)**. These results suggest that positive anticipated emotions seem to facilitate spontaneous behaviour, most likely due to their high degree of personalization and innovation (Kim and Shin 2015), thus, creating an "emotional lift" during farmers' decisions to use smartphones for agricultural purposes (Lee and Shin 2016). Simultaneously, negative anticipated emotions should contribute to increased motivation to use smartphones for capacity development. Such influences of automation have been observed in the past for fear, shame, sadness and anger in smartphone purchase decisions among Iranian urbanites as the linking pin between cognition (attitude, subjective norm, behavioural control) and conation (intention) (Koshkaki and Solhi 2016).

Attitudinal beliefs in form of perceived usefulness **(**0.518***; **H4a+)** and perceived ease of use **(**0.149***; **H4b+)** are found to influence attitude ($R^2 = 0.400$). Thus, concern about extraordinary time, strain and financial effort farmers using smartphones in developing countries may face as part of the digital divide debate cannot be confirmed to be present in farmer's decision processes.

Both trainer readiness **(**0.272***; **H5a+)** and farmer readiness **(**0.447***; **H5b+)** is found to influence subjective norms. These results are in line with results by Cheon et al. (2012) on US college students' ICT usage behaviour regarding trainer readiness. The result on farmer readiness suggests that within the social and professional network, peers have a comparatively greater influence on Indian small-scale farmers' subjective norms. Such findings may seem surprising after capacity development activities in developing countries over the past decades have been

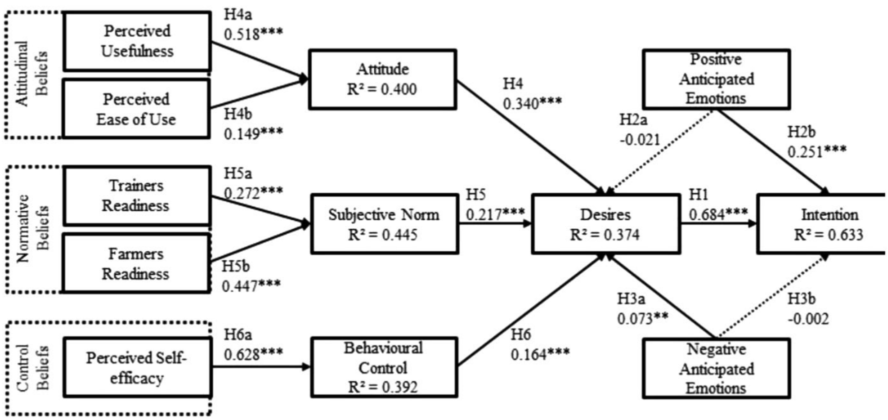

Fig. 2 Path coefficients and R-square-values of the smartphone research model. *Note* $*P<0.10$, $**P<0.05$, $***P<0.01$. *Source* authors own graphic based on Cheon et al. (2012), Perugini and Bagozzi (2001)

predominated by frontal teaching methods, for instance in Farmer-Field-Schools (Phillips et al. 2014). However, such measures may not have reached a large share of the rural population in India, which simultaneously provides an explanation for the importance of group dynamics in these close communities, many of which exist in developing countries' remote areas.

Regarding control beliefs, self-efficacy (0.522***; **H6a+)** is an influential construct of behavioural control. This supports the importance of beliefs in own motivation and ability for smartphone usage. Such self-confidence in connection with the ability to learn autonomously may seemingly help in using a smart-device successfully over distances and amongst the scattered villages in developing countries' remote areas (Aker 2011; Aker et al. 2016; World Bank 2016b). However, since the statements included in the latent variable learning autonomy are negatively phrased, the effect observed is consequently a negative one. This contradictory influence possibly results from differences in the definition of autonomous learning among societies, since corresponding measures have been derived from a study on an industrialized country (Cheon et al. 2012).

Conclusion and implications

This study presents a comprehensive behavioural model for identifying and quantifying the drivers of small-scale farmers´ intention to use a smartphone for capacity development activities in the remote areas of Bihar, one of the poorest regions in India (World Bank 2016a).

The results confirm the conceptual integration of the MGM approach and the models for technological acceptance into the framework and give evidence of its overall applicability in the context of a developing country's agricultural sectors. It explains almost 70% of the variance of farmers' intention to use a smartphone for capacity development purposes, approximately 40% more than averagely observed in other TPB-based studies (Sheeran 2002) and approximately 20% more than the model proposed by Venkatesh and Sykes (2013). The inclusion of the affect (desires and emotions) and its proven relevance as the linking pin between cognition and conation regarding smartphone usage for agricultural purposes (Chhachhar and Maher 2014; Koshkaki and Solhi 2016) represent an especially important finding. The results related to the "affect" suggest the existence of the "emotional lift" during work-specific usage decisions in developing countries' agricultural sectors, independent from the general smartphone usage behaviour under research in earlier studies (Lee and Shin 2016). This finding addresses various stakeholders (e.g. researchers, NGOs and politics) involved in developing measures for the enhancement of sector-wide capacities for modern sustainable farming practices.

From a research perspective, the framework developed in this study provides a valid and reliable basis for future applications in similar settings, especially in the context of developing countries, where the respondents are not used to modern ICT yet and live in close communities with strong social bonds in villages scattered throughout remote areas. Empirical research may offer crucial results for leveraging efforts by politics and NGOs (Aker 2011; Deichmann et al. 2016) not only in supporting the introduction of smartphones monetarily, so that farmers have the possibility to overcome the digital divide and benefit from rapid information access over distances, but also by acknowledging farmers' psycho-economic usage drivers to facilitate the diffusion of the technology in the sector (Venkatesh and Sykes 2013).

The perceived favourability of smartphones for capacity development among farmers should be the special focus of extension programmes. Since Indian farmers seem to prefer initial guiding support when getting started with this technology and attach great importance to the opinion of other farmers, smartphones should be promoted more strongly using village-wide field demonstrations to increase usage-rates. Negative emotions arising from usage failure can thereby function as motivation-triggers as a reflection of ambition (Koshkaki and Solhi 2016) while positive emotions arising from usage success may lead to spontaneous affective usage decisions. Correspondingly, smartphone applications should be designed with user-friendly interfaces for the specific target group of farmers from developing countries.

In further studies, the conceptual framework should be extended by the actual behavioural action to find out if an emotionally lifted intention leads to higher work-specific usage rates. The extended framework should be tested in the context of a country with appropriate smartphone coverage or in an experiment with a distribution of smartphones along with respective applications. In addition, future research could be directed to obtain deeper insights from the refraining perspective to identify the work-specific barriers preventing the growing number of farmers who already own a smartphone from using it for agricultural purposes. Thereby, it could be investigated if specific barriers are associated with negative emotions that do not function as motivation-triggers.

To identify specific user groups among the target group of farmers, socio-demographic characteristics could be included into the current framework by implementing conceptual ideas from the Unified Theory of Acceptance and Use of Technology (UTAUT). The results may help developing smartphone interfaces and applications tailored to the needs of different user-groups among farmers in developing countries.

Finally, to capture learning autonomy appropriately, societal differences between industrialised and developing countries should be accounted for during scale development in future research using the framework developed in this study. Additionally, the framework used in combination with PLS does not allow setting smartphone-based capacity development activities to contrast with other discrete alternatives. In this regard, farmers' preferences for different teaching methods should be further investigated using a choice experimental design.

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Compliance with Ethical Standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

Appendix

See Tables 2, 3, and 4.

Table 2 Means, standard deviations and factor loadings of statements

Code*	Statement	Mean	SD	STD factor loadings (> 0.70)
PU1[a]	I think that using a smartphone would enable me to generate agricultural knowledge more quickly	4.024	0.904	0.801
PU2[a]	I think that using a smartphone would make it more convenient for me to generate agricultural knowledge	4.012	0.805	0.853
PU3[a]	I think a smartphone to generate agricultural knowledge is useful	3.962	0.901	0.829
PU4[b]	Overall, I think that using a smartphone to generate agricultural knowledge is advantageous	4.088	0.791	0.845
PU5[c]	With using a smartphone, I can access information on agricultural practices whenever I need it	4.003	0.866	0.854
PU6[c]	Being familiar with smartphones also enables me to work with other technological innovations	4.014	0.822	0.828
PU7[c]	Agricultural knowledge I could obtain from smartphones is knowledge I need	3.98	0.853	0.829
PEU1[a]	I think that using a smartphone to generate agricultural knowledge would be easy	3.779	1.052	0.740
PEU2[b]	I think that using a smartphone to generate agricultural knowledge does not require a lot of mental effort	3.556	1.069	0.769
PEU3[c]	Using a smartphone to generate agricultural knowledge will save time	4.021	0.867	0.815
PEU4[a]	Agricultural knowledge presented by smartphone applications is much easier to understand than normal training	3.874	0.932	0.814
AT1[d]	Using a smartphone to generate agricultural knowledge will be helpful	3.961	1.015	0.881
AT2[d]	The use of the smartphone as a learning tool excites me	3.874	1.032	0.908
AT3[d]	Using a smartphone for generation of agricultural knowledge would be a pleasant experience	3.92	1.005	0.913
AT4[d]	Using a smartphone to generate agricultural knowledge will make my work more attractive	3.772	1.081	0.904
AT5[a]	I would like the agricultural work more if I would use a smartphone	3.751	1.092	0.866
TR1[a]	I think trainers and experts would be in favour of utilizing a smartphone to generate agricultural knowledge	3.94	0.994	0.892
TR2[a]	I think trainers and experts would believe that a smartphone could be a useful educational tool in their training	3.965	0.852	0.898
TR3[a]	I think trainers and experts would possess adequate technical skills to use a smartphone in their training	3.988	0.88	0.918
FR1[a]	I think other farmers would be in favour of utilizing smartphones in their training	3.902	0.928	0.886
FR2[a]	I think other farmers would believe that a smartphone could be a useful educational tool in their coursework	3.814	0.949	0.877
FR3[a]	I think other farmers would possess adequate technical skills to use a smartphone in the training	3.741	0.97	0.869
SN1[e]	Stakeholders I am working with think I should integrate smartphones to generate agricultural knowledge	3.764	1.131	0.793

Table 2 (continued)

Code*	Statement	Mean	SD	STD factor loadings (> 0.70)
SN2[a]	Most people who are important to me would be in favour of using a smartphone to generate agricultural knowledge	3.625	1.086	0.833
SN3[b]	Other farmers in my surrounding think I should take advantage of smartphones to generate agricultural knowledge	3.691	1.058	0.836
SN4[b]	People whose opinions are valued to me expect that people like me should use smartphones to generate agricultural knowledge	3.678	1.059	0.834
SN5[a]	I think other farmers in my village would be willing to adopt a smartphone to generate agricultural knowledge	3.773	0.989	0.840
SN6[b]	Generally, it is expected of me to use a smartphone to generate agricultural knowledge	3.805	0.966	0.848
SE1[a]	I am confident about using a smartphone to generate agricultural knowledge	3.997	0.886	0.842
SE2[a]	Using a smartphone to generate agricultural knowledge would not challenge me	3.753	1.053	0.800
SE3[a]	I would be comfortable to use a smartphone to generate agricultural knowledge	3.789	0.997	0.859
BC1[b]	I think that I have the discipline to learn how to use a smartphone to generate agricultural knowledge	4.011	0.873	0.890
BC2[b]	My own decisions and actions are decisive whether I will use a smartphone	3.939	0.92	0.870
PE1[d]	If I would succeed to increase agricultural knowledge by the aid of using a smartphone, I will feel Excited	3.287	1.434	0.904
PE2[d]	If I would succeed to increase agricultural knowledge by the aid of using a smartphone, I will feel Delighted	3.431	1.315	0.927
PE3[d]	If I would succeed to increase agricultural knowledge by the aid of using a smartphone, I will feel Happy	3.537	1.26	0.922
PE4[d]	If I would succeed to increase agricultural knowledge by the aid of using a smartphone, I will feel Glad	3.421	1.297	0.920
PE5[d]	If I would succeed to increase agricultural knowledge by the aid of using a smartphone, I will feel Satisfied	3.475	1.323	0.929
PE6[d]	If I would succeed to increase agricultural knowledge by the aid of using a smartphone, I will feel Proud	3.443	1.394	0.889
PE7[d]	If I would succeed to increase agricultural knowledge by the aid of using a smartphone, I will feel self-assured	3.712	1.27	0.875
NE1[d]	If I would NOT succeed to increase agricultural knowledge by the aid of using a smartphone, I will feel Angry	2.035	1.156	0.880
NE2[d]	If I would NOT succeed to increase agricultural knowledge by the aid of using a smartphone, I will feel Frustrated	1.941	1.178	0.895

Table 2 (continued)

Code*	Statement	Mean	SD	STD factor loadings (> 0.70)
NE3[d]	If I would NOT succeed to increase agricultural knowledge by the aid of using a smartphone, I will feel Guilty	1.783	1.151	0.854
NE4[d]	If I would NOT succeed to increase agricultural knowledge by the aid of using a smartphone, I will feel Ashamed	1.925	1.12	0.856
NE5[d]	If I would NOT succeed to increase agricultural knowledge by the aid of using a smartphone, I will feel Sad	2.17	1.158	0.829
NE6[d]	If I would NOT succeed to increase agricultural knowledge by the aid of using a smartphone, I will feel Disappointed	2.261	1.169	0.788
DE1[d]	My desire for using a smartphone in order to increase agricultural knowledge can be described as very strong	3.968	1.029	0.952
DE2[d]	I want to use a smartphone to generate agricultural knowledge	4.021	0.921	0.957
IT1[d]	I am planning to use a smartphone to generate agricultural knowledge	3.847	1.042	0.909
IT2[d]	I will expand efforts on using a smartphone to generate agricultural knowledge	4.002	0.894	0.920

Source authors own data and calculations

[a]Based on Cheon et al. (2012):

[b]Based on Venkatesh and Bala (2008):

[c]Based on Davis (1984):

[d]Based on Perugini and Bagozzi (2001):

[e]Based on Ajzen (1991):

Table 3 Reliability measures of the model constructs

Construct	Abbreviation	Nr. of items	Cronbach's alpha (> 0.70)	Composite reliability (> 0.70)	Average variance extracted (> 0.50)
Perceived usefulness	PU	7	0.927	0.941	0.696
Perceived ease of use	PEU	4	0.799	0.865	0.617
Attitude	AT	5	0.938	0.953	0.801
Trainers' readiness	TR	3	0.887	0.930	0.815
Farmers' readiness	FR	3	0.851	0.909	0.770
Subjective norms	SN	6	0.910	0.930	0.691
Self-efficacy	SE	3	0.782	0.889	0.668
Behavioural control	BC	2	0.709	0.873	0.774
Positive anticipated emotions	PE	7	0.965	0.971	0.827
Negative anticipated emotions	NE	6	0.924	0.940	0.724
Desire	DE	2	0.903	0.954	0.911
Intention	IT	2	0.804	0.911	0.836

Source authors own data and calculations

Table 4 AVE square roots (diagonal) and construct correlations for assessing the Fornell-Larcker criterion

	AT	BC	DE	FR	IT	NE	PEU	PU	PE	SE	SN	TR
AT	**0.895**											
BC	0.450	**0.880**										
DE	0.561	0.407	**0.955**									
FR	0.583	0.462	0.580	**0.877**								
IT	0.538	0.509	0.759	0.596	**0.914**							
NE	0.140	0.037	0.146	0.184	0.157	**0.851**						
PEU	0.519	0.521	0.529	0.643	0.616	0.261	**0.785**					
PU	0.624	0.607	0.644	0.732	0.724	0.195	0.715	**0.834**				
PE	0.466	0.361	0.301	0.460	0.456	0.235	0.363	0.545	**0.910**			
SE	0.621	0.628	0.572	0.618	0.638	0.177	0.646	0.716	0.488	**0.834**		
SN	0.675	0.438	0.518	0.639	0.525	0.110	0.523	0.620	0.399	0.672	**0.831**	
TR	0.657	0.480	0.688	0.706	0.619	0.195	0.562	0.740	0.463	0.635	0.588	**0.903**

Source authors own data and calculations

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