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Factors influencing the use of mobile applications by farmers for data and information management

- A case in North-Western Germany -

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Abstract

Purpose of the research: This research aims to find influencing factors for the use of smartphone applications for data and information management by farmers.

Design / methodology / approach: To this end, a literature study was conducted. It resulted in the development of a quantitative questionnaire. The data, gathered by convenience sampling in the region North-Western Germany, was evaluated by descriptive statistics and binary logistic regression analysis.

Findings: The main findings were that Facilitating Conditions (resources like a mobile device, mobile internet, and knowledge) have the most significant impact on the use. The Performance Expectancy also has a significant impact, whereas the impact of Effort Expectancy was not significant.

Research implications: Surprising was the impact of Social Influence as this was in contrast to literature. The results suggest that social pressure can create a kind of blockade against the use of smartphone applications by farmers. However, this requires further scientific investigation.

Originality value: This study forms kind of a basis for further studies regarding the use of mobile phones by farmers. So far, little is known about the factors influencing farmers' use of smartphone applications.

Keywords: UTAUT, Innovation, Agriculture, Mobile application, Farmer

Executive Summary

This study aimed to identify factors influencing the use of mobile applications for farmers' data and information management. In the literature, there are many results on the adoption and use of new technologies and the development of management systems for agriculture. So far, however, little research has been done on the use of mobile applications by farmers.

For this reason, a literature search was conducted to determine the state of knowledge for this topic. It became clear that the adoption of new technologies in many different economic sectors was the subject of many studies. Venkatesh et al. (2003) took a multitude of existing models as an opportunity to develop and test the unified theory of acceptance and use of technology (UTAUT). This model was applied in this research to the group of farmers and their usage behavior concerning smartphone applications for data and information management.

For peculiarities of the farmers, the study region with its specific agricultural enterprises was defined, and factors that were already proven as influential in existing literature were reviewed.

The following four hypotheses were developed by incorporation of the general model for the adoption and use of new technologies and the individual factors of agriculture as the basis for this study.

H1: *High-Performance Expectancy has a positive impact on the use of smartphone applications for data and information management by a farmer.*

H2: *Low Effort Expectancy about a mobile application has a positive impact on the farmer´s actual use of it.*

H3: *The Social Influence surrounding a farmer has a positive impact on the use of mobile applications.*

H4: *The Facilitating Conditions of a mobile application have a significant impact on a farmer´s actual use of it.*

Based on existing surveys, a questionnaire was developed to investigate the influence of the factors mentioned earlier on the use of smartphone applications for data and information management by farmers. The latent constructs of the hypotheses were measured with different sub-items using seven-point Likert scales. The survey was pretested by two farmers and reviewed by three supervisors.

The questionnaire was scattered over social media (Facebook) and WhatsApp. In this convenience sampling, 89 fully completed questionnaires were collected, of which 72 were included in the evaluation. The answers of the farmers were evaluated using descriptive statistics as well as binary logistic regression (SPSS). The following factors were controlled in the regression analysis to determine

the influence of the individual constructs on the use of smartphone applications: age, education, size of the farm, farming type and intensity, and investments in new technologies in the last five years.

The results of the evaluation clearly show that Facilitating Conditions have the most significant impact on the use of smartphone applications as they are a prerequisite. In literature, Performance Expectancy was identified as the most significant influencing factor. In this study, this factor had the second most potent influence. A positive correlation was found between a lower Effort Expectancy and the use of applications, but its influence was not statistically significant.

Surprising was the result of the Social Influence since this factor, in contrast to the literature, showed a negative correlation between social desirability or social pressure and the use of smartphone applications. This relationship requires further scientific investigation.

In general, it can be stated that the sample is not representative of the region. The participants were significantly younger, better educated, and manage larger farms than the average of the study region. For this reason, the transferability of the results to the study region is debatable despite statistically significant influences.

For the sample, however, the connection between Facilitating Conditions, such as the availability of necessary resources (smartphone, internet connection, and knowledge for use), is the most significant influencing factor. Positive performance expectations for the use of an application have the second-largest influence and significantly increase the probability of use.

More detailed information can be found in the following paper.

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List of Abbreviations

AU	Attitude Towards the Use
CF	Conceptional Framework
DSS	Decision Support System
DST	Decision Support Tool
EDU	Education
EDU_high	Education high (more than three years of agricultural education)
EE	Effort Expectancy
EE_Mean	Mean of Effort Expectancy Construct Items
EU	Ease of Use
FC	Facilitating Conditions
FC_Mean	Mean of Facilitating Conditions Construct Items
FI	Farming Intensity
FMIS	Farm Management Information System
FMS	Farm Management System
FT_high	Farming Type high (more than two branches managed on-farm)
GVE	Livestock Density in Livestock Units
ha	Hectares
ICT	Information and Communication Technologies
IDT	Innovation Diffusion Theory
IoT	Internet of Things
IT	Information Technology
kg	kilogram
LS	Lower Saxony
MIS	Management Information System
MS	Münsterland-Region
NRW	North Rhine Westphalia
PA	Precision Agriculture
PC	Personal Computer
PE	Performance Expectancy
PE_Mean	Mean of Performance Expectancy Construct Items
PU	Perceived Usefulness
SCA	the Scale of Farming (Cultivated Area)

SF	Smart Farming
SI	Social Influence
SI_Mean	Mean of Social Influence Construct Items
SPSS	Statistical Package for the Social Sciences
TAM	Technology Acceptance Model
TF	Type of Farming
TI	Technology Investments
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
WE	Weser-Ems-Region

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1. Introduction

The introductory chapter gives an overview of the topic of this work. First, the background of the problem is described and gradually reduced to the problem definition. Then the aim of this work is described, and the main research question, as well as sub-questions, are defined. In the following section, the research framework is explained with which the main research question is to be answered. At the end of this chapter, the key concepts are defined, and an overview of the structure of this report is given.

1.1. Background

Modern agriculture faces many challenges. New laws and regulations, an uncertain economic future, changing consumer demands (Eichler Inwood & Dale, 2019), a growing world population (FAO, 2009a), and a reduction in arable land are affecting the development of many farms (FAO, 2009b). The population growth is potentially reaching 8.5 billion in 2030 and 9.7 billion people in 2050 (Ribeiro, 2015). Additionally, a change in consumption habits, i.e., more protein consumption, will lead to an increase in food demand by more than 70 percent compared to today (FAO, 2009a; WHO, 2003). On the other hand, society puts pressure on farmers to reduce the environmental impact of farming methods (Balmann & Schaft, 2008). By the use of big data and the resulting efficiency improvements, food issues like food security, safety, scarcity, and sustainability can be addressed (Deloitte, 2016; Wolfert, Ge, Verdouw, & Bogaardt, 2017).

At the same time, the structural change in agriculture continues. The number of farms decreases while the size of each farm grows (Balmann & Schaft, 2008; Kaloxylos et al., 2012). As farms grow, so does the complexity of their management. The farmers collect the data to manage large and complex farms either themselves in their operation, or analog or digital. Some information is made available to the farmers via many different channels, e.g., e-mail, newsletter, television, smart applications, sensors, or advisers (Kaloxylos et al., 2012).

New Internet of Things technology (IoT) and smart devices, often referred to as “Farming 4.0”, offer the possibilities to collect a vast amount of data on-farm and off-farm. This data is used to give the farmer support in evidence-based decisions to handle the growing complexity of farm management (Verdouw, 2016). By the use of these precise technologies, farmers can reduce the ecological footprint of their farm activities as well as increasing the efficiency. Nevertheless, many farmers are recently experiencing an information overload because of the information-rich datasets in different formats offered by different platforms and channels (Fountas et al., 2015; Sørensen et al., 2010). Farm management and information systems try to collect, order, process and visualize the data to help the farmer by managing the vast amount of information and make an evidence-based decision (Pham & Stack, 2018; Rose et al., 2016).

For this purpose, many different software programs have been offered so far. However, frequently, these programs have been offered as island solutions for unique ranges by different manufacturers (Eichler Inwood & Dale, 2019; Fountas et al., 2015). Modern farm management systems (FMS) and decision support tools (DST) aggregate and combine different software solutions. They provide farmers with information for evidence-based decision making (Rose & Bruce, 2018). Until now, however, this information was only available in the agricultural office after extensive data collection (Fountas et al., 2015). The data collected to run these systems can be general data on finances, governmental rules, and regulations. It can also be specific data about pricing, crop conditions, fertilization, climate, the herd, or accounting. In general, there are infinite possibilities to collect data in farm businesses.

With the advent of smartphones and other mobile devices, information can be captured quickly and easily and retrieved anytime, anywhere (Szilagyi & Herdon, 2006). There is no need to keep lists and manually transfer data to the management programs. These time-consuming data transmission, which can lead to transfer errors, can be entered into the programs by smart connected devices or by direct input via app usage (Deloitte, 2016).

However, many farmers still use handwritten lists and evaluation sheets for data collection as a basis for their decisions (Rose et al., 2016). This behavior is not very efficient and can lead to wrong decisions as the capability to handle big datasets is not given. Recent scientific literature focused on the development of farm management information systems (FMIS) to support farmers in their daily decision making. These studies did not take the influence of different devices to use these programs into account. There are only a few studies that examine the adoption, and use of mobile applications for data and information management by farmers as this topic only came up the past five years. These mobile applications can be crucial to farm management. They can improve farmers decision making to cope with structural changes, face the future challenges of increased food demand, foster efficiency improvements, and reduce the ecological impact of farming. Despite these many arguments for the use of smartphone applications, these are so far little used by farmers. For this reason, in this thesis, factors are examined that influence the use of mobile applications to support farmers in their daily data and information management.

1.2. Research Objective and Main Research Question

Research found that farmers are feeling ever-increasing pressure. Economic constraints, as well as social requirements and changing environmental conditions, require faster and more specific decisions (Deloitte, 2016). Efficiency and sustainability play a significant role here. However, it is also essential to meet the requirements for legal documentation obligations and regulations (Godfray et al., 2010).

For this reason, the complexity of farm management, the associated decisions, and record-keeping tasks are continually increasing. To make decisions not solely from the gut and to cope with documentation requirements, farmers collect data. This data can be about their soil and livestock, rainfall, costs and revenues, consultant information, and many other variables that influence their decisions (Carrer, Souza Filho, Batalha, & Rossi, 2015). Until now, this data has often been collected manually and sometimes fed into the various separated management programs. They are evaluated individually to make decisions for single business areas (Eichler Inwood & Dale, 2019). Recent research was focused on the development of farm management information systems that integrate various isolated solutions into a single program. Data is collected automatically by sensors as well as manually by the farmer or consultant. Modern smartphones offer the possibility to make data available anytime and anywhere to support the farmer in his decisions (Szilagyi & Herdon, 2006). In the literature, many factors are stated that influence the adoption of FMIS, but these still lack adoption.

The unified theory of acceptance and use of technology (UTAUT) classifies influencing factors for technology adoption into the following categories. Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). PE describes the expectation someone has of the use of a new product. EE describes the expected effort someone has to invest in learning how to use new technology. The expectations of the social environment regarding the use of new technology, as well as the conditions that enable its use, are summarized in the categories SI and FC. (Venkatesh, Morris, Davis, & Davis, 2003)

Researchers also found that many farmers do not use mobile phones for decision making and data management (Rose et al., 2016). Recent scientific literature focused on the development and adoption of FMIS and precision agriculture (pa-) technology. So far, however, few studies are known about the factors influencing the use of smartphones and the adoption and use of applications installed on them for data and information management in everyday agricultural work.

This gap in the literature brings us to the specific research question:

Which factors influence the use of a mobile application for data and information management by farmers?

The following sub-questions are formulated to answer the main research question:

1. *Does Performance Expectancy have an impact on the use of smartphone applications for data and information management by a farmer?*
2. *Does the Effort Expectancy about a mobile application have an impact on farmer's use of it?*
3. *Does the Social Influence surrounding a farmer have an impact on the use of mobile applications for data and information management?*
4. *Do the Facilitating Conditions of a mobile application have a significant impact on a farmer's actual use of it?*

The objective of this research is to identify factors that influence the use of mobile applications by farmers for data and information management. With this information, politicians, scientists, and software-companies can help farmers to cope with environmental problems, comply with regulations, and increase operational efficiency to improve the sustainability of modern agriculture.

The region North-Western Germany was selected for this study. Family-owned farms characterize it with very livestock intensive management as well as substantial technological progress further described in chapter 2 (BMEL, 2017).

1.3. Research Framework

A research framework is an overview of the research objective and describes the steps that need to be taken to achieve it (Beech, 2015). The research framework of this project is presented in Figure 1.

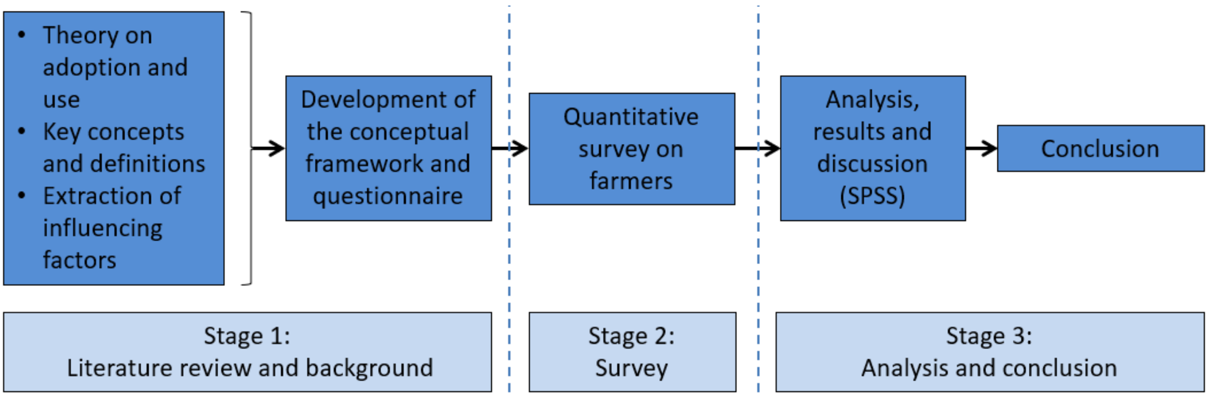

Figure 1: Research Framework – Use of Mobile Applications by Farmers

In the first step, a literature study will be carried out. The literature research serves to find out factors significantly influencing the use of similar technologies, e.g., the introduction of computers, farm management information systems, or smart farming. In the second step, an online survey will be conducted to examine the determinants of the use of mobile applications for farmers' data and information management. Based on the evaluation of the survey results with SPSS, it will be examined whether the factors have the same positive or negative effect on the use of smartphone applications. Moreover, it analyzed which factors have the most considerable influence. In the final step, a conclusion is made to answer which factors need to be emphasized to promote the use of mobile applications for data and information management in agriculture. This conclusion is particularly crucial for app vendors as they can boost sales of mobile applications. For policy-makers, better data collection and analysis offers the opportunity to address environmental issues and increase food security through traceability. For farmers, the use of applications can lead to time savings and increased operational efficiency and, thus, profitability.

1.4. Definition of Concepts

FMIS: A Farm Management Information System is defined after Sørensen et al. (2010) as a system to collect, process, store, and disseminate data in a form that helps to carry out farm operation. This research is based on all software applications that provide the farmer with information or help the farmer with collecting data for his farm management. It includes weather or price applications, record-keeping instruments, advisory applications, or news tickers.

Mobile application: A mobile application is a software program that is installed on a smartphone, tablet to collect data, transmit information, or control sensors and processes. These applications allow data to be captured at the point of origin. With mobile applications, information, communication, interaction, and transactions can take place via mobile devices and corresponding networks (Own Definition after Gabler Economic Lexicon: Key Words: Application, Mobile Business, Mobile Computing, Mobile data acquisition) (Gabler, 2018c, 2018d, 2018a, 2018b).

Farmer: In this study, all persons who collect and manage data and information on a farm are regarded as a farmer. In larger farms, this can also include employees or in smaller farms, family members that work on the farm who are responsible for individual subareas, and deal with data. According to the Agricultural Structure Survey 2016, an average of three workers works on each farm, of whom 48 percent are family workers (BMEL, 2017). Thus, on average of all farms in Germany, the farmer is not alone on the farm, but also half an additional family labor force and one and a half external workers are employed. These additional workers also collect and process data on the farms and are therefore part of this study.

Data and information management: Data is the raw form of unprocessed unsorted information. Data and information management describes the processing and preparation of these raw data into useful and usable information. The processes of information management consist of collecting, sorting, storing, distribution, and use. Information management makes enterprises more efficient and competitive, as they are better informed and can make better strategic decisions (Detlor, 2010).

North-Western Germany: In this research, this regional distinction comprises the northwest of the federal state of North Rhine-Westphalia (NRW), named "Münsterland" (MS), and southwest of Lower Saxony (LS) named "Weser-Ems"-region (WE). These regions are defined by the first two postal code numbers 48 for MS in NRW and 26 and 49 for WE in LS. The German postal code consists out of five numbers, where the first two numbers define the region, and in combination with the following three numbers, the city or village is defined.

1.5. Report Structure

This introduction is followed by a review of the literature on the current state of knowledge. The study region is defined in more detail. Then the barriers, as well as enabling factors, are presented. The conceptional framework (CF) is derived from the literature overview in chapter two. The questionnaire for the survey has been developed based on the CF. In chapter three, the materials and methods used in this research will be explained in more detail. Besides, the conduct of the survey, as well as the data analysis and evaluation, are explained. In chapter four, the results are presented. Then they are compared with the existing literature in the discussion in chapter five. Chapter six consists of conclusions and limitations. The cited works are listed in the bibliography. The questionnaire and additional tables are presented in the appendix.

2. Literature Review

In the following paragraph, an overview of the research region is given. This is followed by a description of different models to explain the adoption intention and use of new technologies. In the next part, factors that influence the adoption of new technologies in agriculture are reviewed. The following paragraph combines the influential factors in agriculture with a general model on adoption intention and use and finally results in the CF of this research, which is explained in the last part of this chapter.

2.1. Agriculture in North-Western Germany – The Research Region

According to the results of the Agricultural Structure Survey 2016, there were 275,400 farms in Germany, with an area of 16.7 million hectares (ha). With the structural change to ever-larger production units, the number of farms has steadily decreased in recent years. From 2013 to 2016, the number of farms in Germany decreased by 3.4 percent (about 9,600 farms) (Destatis, 2019a).

In this paper, the regions WE and ML, marked in red in Figure 2 in the northwest of Germany, are investigated. In the WE-region, there are about 17,500, and in the ML-region, there are 9,130 farms in 2013 (Statistisches Bundesamt, 2014). These two regions account for 9.7 percent of all German farms. The average farm size is 52.8 ha for WE and 36.0 ha for ML (Statistisches Bundesamt, 2014).

The regions WE and ML are characterized by livestock intensive farms indicated by brown color in the overview of livestock density in livestock units (GVE) per ha in Germany. The GVE is a conversion key for comparing different livestock based on their live weight. One livestock unit corresponds to about 500 kilograms (kg) of live weight (LSN, 2019). In the regions WE and ML, the density is between 1.4 to 3.0 GVE/ha. These numbers correspond to a live weight of 700 to 1,500 kg/ha, which is very high compared to the rest of Germany. Only a few districts in Bavaria and Schleswig Holstein have similar livestock densities.

In earlier times, in the 19th century, the regions with their poor sandy soils and small-scale subsistence agriculture were regarded as the poorhouse of the Federal Republic of Germany. Since industrialization and the green revolution, the image of this region has changed dramatically (Otten, 2013).

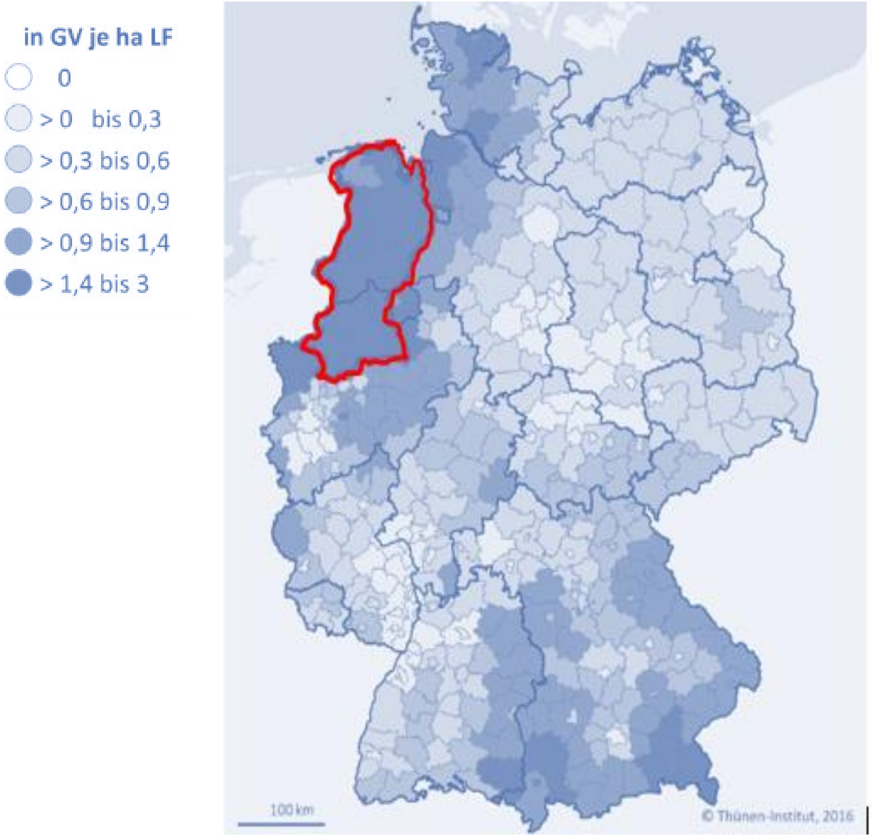

Figure 2: Overview of Livestock Density in Livestock Units per Hectare in Germany in 2016 (Agethen, 2018)

The proximity to the coast and its ports has made it possible to import fertilizers and feed cheaply. Through economies of scale, increased profits, and the establishment of an agricultural cluster of upstream and downstream companies, the region underwent a structural change. Especially animal husbandry progressed faster than in any other part of Germany (Bäuerle, 2008 in Otten, 2013). Today, the region is regarded as the “Silicon Valley” for agriculture and the food industry (Windhorst & Grabkowsky, 2007). The expansion of livestock has been accompanied by specialization and intensification of production, which has led to competitive advantages and the expansion of the region into the center of the processing industry (Bäuerle, 2008 in Otten, 2013). Through its network and cluster formation with upstream and downstream companies, the region also occupies an essential position in the international agricultural sector (Deimel & Theuvsen, 2010; Spiller & Schulze, 2008).

Together with the region, individual farms also underwent rapid changes. They made the way from a subsistence economy with family workers to large business units with external consultants and external workers as well as the automation of many on- and off-farm processes. By adopting new technologies, farm managers have increased their efficiency and adapted their farms to future challenges (Windhorst & Grabkowsky, 2007). These farmers with a high degree of automation are experienced in the adoption and use of new technologies (BMEL, 2017).

The structural change, the decreasing number of farms and the higher degree of mechanization, lead to a decrease in the number of farmers. The remaining farmers have an older age structure than the average for non-agricultural sectors in Germany in 2016 (DBV, 2019). Within agriculture, farm managers in Germany are on average older than their colleagues in Eastern Europe, but younger than those in Southern Europe. The average age of farm managers in Germany in 2013 was 53 years (Deter, 2013).

Not only the age structure and the number and size of farms but also the educational level of farmers is changing. The proportion of farm managers who have attended a master school or a university degree is growing. According to the results of the Agricultural Structure Survey 2016, 65 percent of all farm managers have completed agricultural vocational training. Of these farmers, 12 percent have a university degree (Destatis, 2019b). The proportion of farmers who have a university degree especially increases for younger farmers (Fischer, 2017).

2.2. Theory on the Use of New Technology

The use of new technology is the subject of many studies. Various models have been developed to determine factors influencing the intention to adopt or use new technologies. Some relate to personal factors, others to organizational factors, or environmental factors influencing the adoption intention and use of innovation.

One of these basic models is the theory of reasoned action (TRA), developed by Fishbein and Ajzen which is a model for predicting behavior based attitudes and subjective norms (Ajzen & Fishbein, 1977). The TRA is one of the most fundamental and influential theories of human behavior and is based on social psychology (Venkatesh et al., 2003).

Another basic model is the theory of planned behavior (TPB), which was proposed in 1985 by Ajzen as an extension of the TRA (Ajzen, 1991). This theory adds motivation as perceived behavioral control to the constructs of attitude and subjective norm. Attitude refers to the fact that a person perceives the proposed behavior as positive. The subjective norm describes that one person thinks the other wants them to behave in a certain way. These two behaviors result in higher motivation and, thus, the intention of adoption (Ajzen, 1991; Venkatesh et al., 2003).

The innovation diffusion theory (IDT), developed by E. M. Rogers in 1961, is also rooted in sociology (Rogers, 1961). Based on the IDT and TRA, Moore and Benbasat developed seven core constructs to investigate the diffusion of information systems. The following constructs were evaluated: Relative advantage, ease of use, image, visibility, compatibility, result demonstrability, and voluntariness of use (Moore & Benbasat, 1996).

The technology acceptance model (TAM) was developed by Davis and is based on the TRA (Davis, 1985). This model makes a statement on a person's technology use or refuse. The TAM is based on the assumption that the attitude towards the use (AU) of a technology depends on two variables: Perceived usefulness (PU) and ease of use (EU) (Davis, 1985). PU describes how the use of technology can improve a person's work performance. EU, in turn, describes a person's perception of how much effort is needed to learn to use the new technology. The model also analyzes the intention to use, which is dependent on the PU and AU (Davis, 1985). In 2000, Davis and Venkatesh extended the TAM to include the constructs of the Social Influence and cognitive process groups and named the model TAM2 (Venkatesh & Davis, 2000).

In 2003, Venkatesh et al. used a large number of models developed with overlaps and differences in the variables and constructs investigated to develop the unified theory acceptance and use of technology (UTAUT) shown in Figure 3**Fehler! Verweisquelle konnte nicht gefunden werden.**. Based on the models described above and other models, they have evaluated and unified the different constructs into one model.

They found out that four basic constructs are the main determinants for the usage and acceptance behavior towards new technologies:

Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). These four constructs are moderated by the factors of gender, age, voluntariness, and experience (Venkatesh et al., 2003).

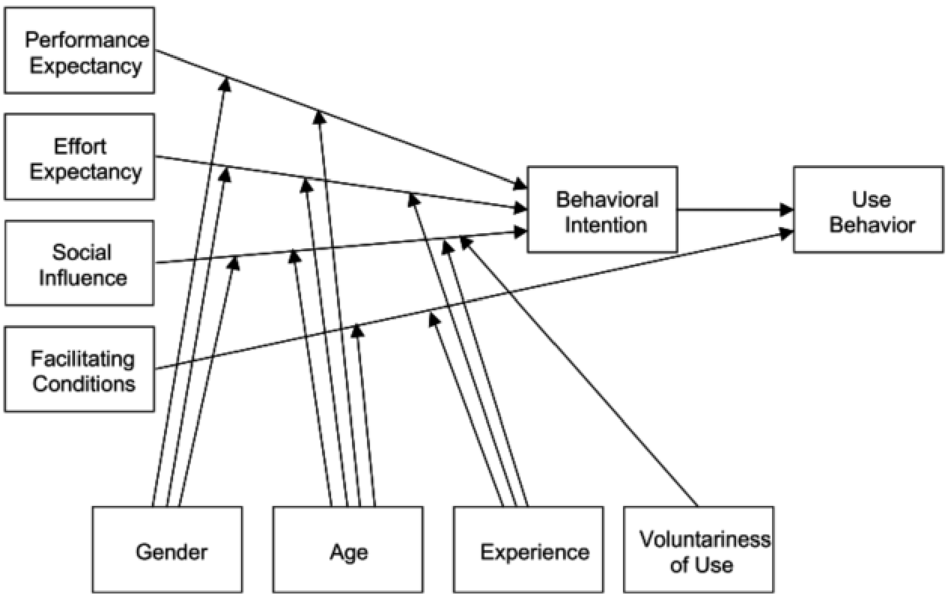

Figure 3: Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003)

PE is defined as: "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). PE is the strongest predictor of intention to adopt (Venkatesh et al., 2003).

EE is described as the perceived ease of using a new system. SI is defined as: "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003). The perception of the organizational structure and equipment that enable the use of the new technology are recorded under FC (Venkatesh et al., 2003).

The moderating variables have different influences on the main constructs. While age influences all main constructs, voluntariness only affects Social Influence. Experience moderates EE, SI, and FI. Gender moderates PE, EE, and SI (Venkatesh et al., 2003). The UTAUT model builds the foundation for this research.

2.3. Factors Influencing the Use of New Technology in Agriculture

Many factors influencing the use of new technology by farmers are cited in the literature. Studies often investigated the adoption of computers by farmers or the use of Farm Management Information Systems (FMIS). These studies use different names to describe a tool or system that collects and aggregates data to help farmers make decisions (Fountas et al., 2015). Common names are Farm Management System (FMS), Management Information System (MIS), Decision Support System (DSS) (Rose & Bruce, 2018) or Decision Support Tool (DST) (Rose et al., 2016). These tools and systems combine the ability to aggregate data from multiple sources and merge them into a complex structure to support decision making. All of these Ag-Tech industry programs belong to the precision agriculture (PA) and smart farming (SF) subdivisions, as they are designed to optimize production and increase the efficiency of agricultural operations (Pivoto et al., 2018). All these tools belong to the field of information and communication technologies (ICT).

With the advent of mobile phones in 2007, the rapid spread of these devices and the applications installed on them, farmers and businesses have achieved entirely new possibilities for data collection, use, and presentation (Jayaraman, Yavari, Georgakopoulos, Morshed, & Zaslavsky, 2016; Köksal & Tekinerdogan, 2018). Currently, around 78 percent of all adults in Germany use a smartphone (Bitcom, 2017). Many farmers are included who use devices not only for private purposes but also for business communication and management (Schlee, 2014). In general, the smartphone fits in very well with everyday agricultural life, since most processes in agriculture are mobile and a device must, therefore, be available for data collection that supports this mobility (Schlee, 2014). A PC in the agricultural office is only available in one place. The restriction of mobility requires the maintenance of lists at the place of data collection, i.e., outside on the field or in the barns. These lists are later manually entered into the software to receive information for farm management. It takes much time, farmers and advisers do not have. Additionally, transfer mistakes can be made quickly (Schlee, 2014).

Through qualitative and quantitative interviews with farmers in the United Kingdom, Rose et al. (2016) have identified fifteen different factors that convince farmers to use FMIS. These include usability, cost-effectiveness, performance, user relevance, compatibility with compliance demands, farming type and scale, peer recommendation, farmer-advisor knowledge transfer, privacy and data security, integration between different systems as well as internet connectivity. Other important user characteristics are age and habit, as well as trust in the company that offers the software (Rose & Bruce, 2018).

For farmers, the cost-benefit effect is decisive for the use of FMIS. This effect is influenced by the factors usability and relevance for the user, namely the possibility to adapt the system to its personal needs, as well as the farm orientation and size (Rose et al., 2016). Besides, a FMIS for data management is more interesting for large farms, as the investment can be compensated more quickly (Rose et al., 2016). Privacy and data security were highlighted as a critical factor for the adoption of new technologies in a study (Wolfert et al., 2017). Farmers fear that their data is misused, e.g., by competitors. Many applications or systems are still fragmented (Pivoto et al., 2018). The data is collected and managed by different manufacturers or devices. Therefore the data is not available for the exchange between different applications (Eichler Inwood & Dale, 2019; Fountas et al., 2015; Tummers, Kassahun, & Tekinerdogan, 2019).

Also, sociodemographic factors have a significant impact. Several studies have highlighted that the age of farmers has a negative influence on the willingness to use new technologies (Hasler, Olfs, Omta, & Bröring, 2017; Rose et al., 2016). The older the farmer and the more farming experience he has, the less willing he is to try new technologies. Younger farmers, on the other hand, are less experienced and can benefit from the support of new systems (Rose et al., 2016). Their planning horizon for using the new technology is longer than the planning horizon of older farmers (Rose et al., 2016).

According to the study by Rose et al. (2016), habits play a significant role. Farmers who are used to try new technologies and to deal with change will integrate new technologies more quickly into their daily work.

This study also points out that individual factors can compensate for other factors. It shows that compatibility with compliance demands is more important to farmers than user-friendliness (Rose et al. 2016). The study of Rose et al. (2016) shows that even a small amount of money can inhibit the use of mobile applications, as even small costs can be a significant burden for small farms.

In contrast, the study of Bonke, Fecke, Michels, and Musshoff (2018) points out that farmers are willing to pay for mobile applications if they deliver value to them. However, it is not always possible to quantify these benefits in monetary terms. This study also highlights that farmers are willing to try new software. They buy it if the purchase is promoted by the government, as this reduces the financial risk of a wrong purchase and high financial burdens (Bonke et al., 2018).

Further studies show that education has a positive influence on farmers' use of new technologies (Carrer et al., 2015). Better educated farmers see more excellent benefits in data collection through new software and technologies. The personal assessment of a farmer´s agricultural skills also plays an important role. Overconfidence has a positive influence on the willingness to use, as the farmer has high expectations of himself and the use of the new technology (Carrer, Souza Filho, & Batalha, 2017). Nevertheless, this study also shows that existing contracts with consulting firms or software providers inhibit the adoption and use of later technologies. The behavior can be due to the previously described habits in daily work processes, as well as the additional costs for familiarization with and conversion to a new system.

2.4. Factors Influencing Farmers Technology Use and UTAUT

In their study, Rose et al. (2016) applied UTAUT to agriculture and investigated the use of DST and FMIS technology by farmers.

The UTAUT model was modified for this purpose. The moderating variable of voluntariness was removed from the model, as farmers are independent business owners. It means farmers can decide voluntarily on the uptake and use of new technologies, which is different from employees that can be forced by the company they work for (Rose & Bruce, 2018). Only government guidelines on documentation requirements could force farmers to use new technologies. However, since documentation is currently still almost exclusively in paper-based form, it can be assumed that the use of new technologies to handle compliance demands is voluntary (Rose et al., 2016).

Besides, the core constructs have been more differentiated to map the distinctive features of agriculture more precisely. The behavioral intention was renamed to uptake and served further as a proxy for the use (Rose et al., 2016).

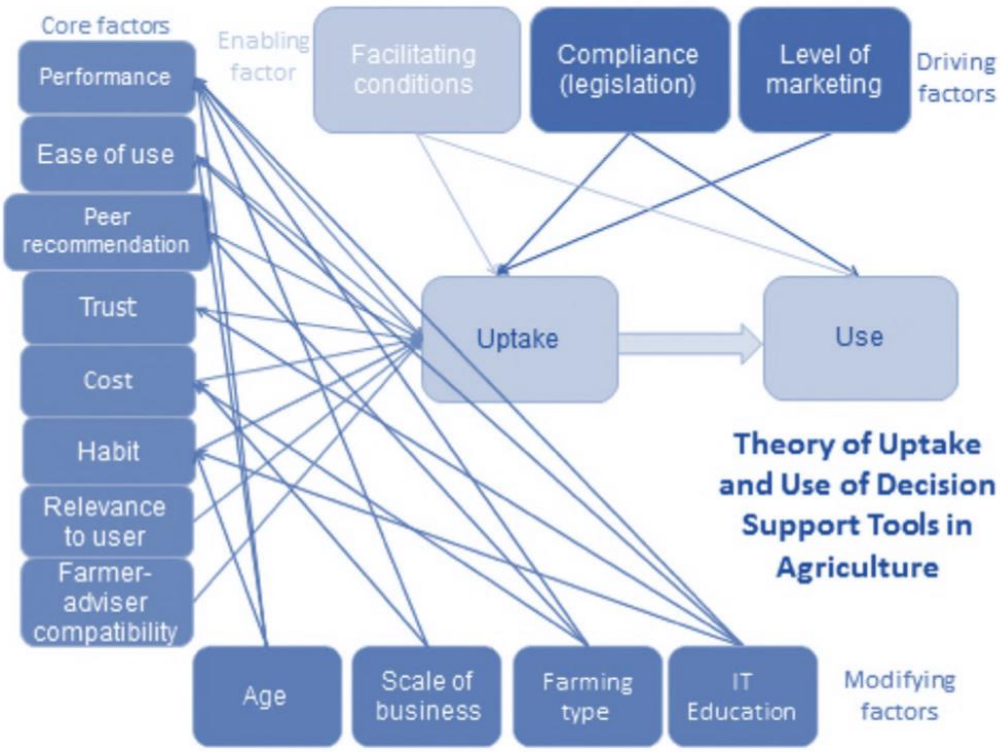

Figure 4: Theory of Uptake and Use of Decision Support Tools in Agriculture (Rose et al., 2016)

For the main constructs, PE was split up into performance and relevance to the user. EE is called ease of use in the modified model, and the constructs' habits and costs are also added. The SI construct is split into peer recommendation, trust, and farmer-advisor compatibility. These three original constructs and their sub-factors are merged in the group of core factors. The construct of FC becomes enabling factors. The constructs of compliance and the level of marketing are driving factors for the uptake and use of new technologies, as shown in Figure 4 (Rose et al., 2016).

The extension of the moderating variables by the size of the company, as well as the type of farming, IT education, and farming experience, was made to respond to the specific needs and characteristics of farmers. Gender is left out as still most of the farms are managed by men (Rose et al., 2016).

2.5. Conceptual Framework

This literature review of different studies focusing on general adoption models and factors influencing the uptake and use of computers and farm management information system builds the basis for the conceptual framework of this research.

Smartphones and mobile applications can be seen as similar path-breaking new technology. This research uses some of the aforementioned factors to investigate the use of mobile applications for data and information management by farmers. For this research, the UTAUT model is applied to analyze the factors that influence farmer's technology use.

The conceptual framework consists of four main constructs influencing the adoption of mobile applications. Each construct has several measurement items which load onto the different construct. The measurement items (shown in brackets) represent single characteristics and factors found in the literature that influence the use of mobile applications for data and information management. The four constructs investigated in this study are the Performance Expectancy (PE) and Effort Expectancy (EE), the Social Influence (SI), and the Facilitating Conditions (FC). The technology investment (TI), farming intensity (FI), type of farming (TF), and scale of farming, as well as age (AGE) and education of farmer (EDU), are used as control variables. The use (U) of mobile applications is the dependent variable.

The application properties mainly define PE. It is the central construct that determines the use of new technology. The probability of using an application that meets the farmer's expectations (PE_8) and solves or simplifies an existing problem is high (PE_1; PE_5; PE_6). However, the application must provide added value over other existing data collection solutions (PE_3; PE_4) (Rose et al., 2016; Rose & Bruce, 2018). Another essential point for a farmer is to stay in line with compliance demands (Wolfert et al., 2017). The demand of the population for sustainable agricultural management is becoming ever higher (Balmann & Schaft, 2008). New regulations and laws are making the work of farmers ever more complex (Eichler Inwood & Dale, 2019). To handle this complexity, the farmer needs both personal support from consultants and technical support from administrative programs (PE_2; PE_7). The factors in the literature lead to the first hypothesis for the use of a mobile application for data and information management by farmers:

H1: *High-Performance Expectancy has a positive impact on the use of smartphone applications for data and information management by a farmer.*

The second construct is EE. This cluster describes the effort a farmer needs to learn the usage and apply the app for farm management. The app needs to be adjustable to particular farm purposes (EE_4) and must be easier to use than existing solutions (EE_2) (Rose & Bruce, 2018). There is a difference in ease of use between single solution applications and extensive applications with many fields of use (EE_1) (Ugochukwu & Phillips, 2018). The ease of use is determined by the time which needs to be invested in learning the usage of new technology (EE_3). These factors lead to the second hypothesis:

H2: *Low Effort Expectancy about a mobile application has a positive impact on the farmer’s actual use of it.*

The construct SI is defined by the network of a farmer (SI_1). Peer recommendations and expectations of people in the farmer's environment have an impact on the use of mobile applications (SI_2). The farmer-advisor compatibility also has a significant impact on the use as both of them exchange much information (Rose et al., 2016) Positive recommendations by other farmers or advisors improve the use of the mobile application by a farmer (Rose et al., 2016). It is also vital that the farm allows working with mobile applications (SI_3) and supports the use of applications for data and information management (SI_4). It means that the farmer and other persons who work on the farm are open to new technologies. It leads to the third hypothesis:

H3: *The Social Influence surrounding a farmer has a positive impact on the use of mobile applications.*

Other important characteristics that influence the use of a mobile application are the resources. A mobile phone or tablet with good internet access is a necessary condition for the use (FC_1) (Rose et al., 2016). Not only the resources but also the on-farm infrastructure is an enabler for the use of mobile applications. Farmers that invested in new machinery and farm equipment are more likely to use new technologies (Wolfert et al., 2017). New machinery equipped with sensors and interfaces to collect data and transmit it to other software tools for management purposes enables the farmer to reduce manual data collection (FC_3) (Wolfert et al., 2017). These farmers require efficiency gains to cover the costs of their investments. The use of smartphone applications to collect and manage the data can support these efficiency gains (Sonka, 2014). Applications that have standardized interfaces with farm equipment offer higher usability (Köksal & Tekinerdogan, 2018; Tummers et al., 2019). A useful application captures data from and delivers data to many different operations and decisions (Köksal & Tekinerdogan, 2018). It prevents doubled data collection and thus saves work for the farmer (FC_2). As farmers work with sensitive data of their farm, the security of data is an important issue for them. Misuse of data is seen as one of the significant barriers to the adoption of smart farming and FMIS (Pivoto et al., 2018). Farmers want clear rules on who can store and process their data and who owns it. Since the data is sensitive farm data, property rights should be with the farmer (Wolfert et al., 2017). To this end, farmers need to reach a specific person if there are problems with an application (FC_4). Additionally, the companies in their terms and conditions for app use and the state must create the legal framework to achieve the highest level of data security, reduce reservations and concerns and thus promote the use of new technologies (Sonka, 2014). The following hypothesis arises from these factors:

H4: *The Facilitating Conditions of a mobile application have a significant impact on a farmer's actual use of it.*

The impact of the four constructs PE, EE, SI, and FC on the use is influenced by the demographics of a farmer and his farm. These factors do not have a direct influence on the adoption intention but can influence the strength of the core constructs (Rose et al., 2016; Venkatesh et al., 2003).

Many studies found that demographics have an impact on user behavior (Hasler et al., 2017; Rose et al., 2016). One factor is the farmers' age (AGE). Rose et al. (2016) found that older farmers use their experience to make farm management decisions, whereas younger farmers are more willing to use new technology to make informed decisions. Older farmers also have shorter planning horizons than younger ones, which makes the use of new technologies more interesting for younger farmers (Roberts et al., 2004; Rose et al., 2016; Rose & Bruce, 2018). The time to cover the costs of new technology is longer.

Farmers' education also plays a significant role (EDU). Better educated farmers allocate more value to a comprehensive dataset to base their decisions on than lower educated farmers do (Carrer et al., 2017). They are better informed about new technology and value the improvements in data and information gathering by IoT-technologies (Roberts et al., 2004). Overall, general education is not the only influencing factor. IT education plays a crucial role. Older farmers often have less experience with PC and smartphones and state that they feel they are not able to use these new devices (Rose et al., 2016). Research showed that good experience with existing IT technologies positively influences the attitude towards new technologies (Rose & Bruce, 2018).

The impact of demographic characteristics of the farmer on the use of new technology was already subject to many studies, and significant impacts of age and education were found. This study controls for the impact of these factors on the core constructs.

Rose et al. (2016) also investigated the modifying impact of farm characteristics on the different core factors. Farms are very diverse (Rose et al., 2016). The size of farmland or the number of animals grown on a farm can vary highly. Some intensive livestock farms even have no farmland (Tey & Brindal, 2012). Other farmers do low intense farming and collect only data necessary to fulfill government regulations. These circumstances offer many different possibilities of management decisions and the underlying data collection (Carrer et al., 2015). Livestock intensive farming offers the possibility to collect such information, e.g., feed intake, performance, birth rates, sickness, and activity levels are only a few parameters (Rose et al., 2016). Farmers that collect a vast amount of data on their farms and therefore spend much time on the maintenance of lists and management programs are more likely to use specialized apps and programs to collect and manage their data (Tey & Brindal, 2012). Besides, the cost-benefit effect for these farms is better than for low-intensity farming. High intense farmers spend much time on the collection of data for management decisions to improve their efficiency (Fountas et al., 2015). The reduction of time to collect data for informed decisions can lead to a competitive advantage. In this research, the farming intensity (FI) is used as a control variable.

As Rose et al. (2016) did only cover arable, dairy, low land grazing, and less favored area grazing (sheep), they propose to research the influence of chicken or pig production on the user behavior of new technology. This research also adds the farm type of renewable energy production as a control variable to the model.

An additional control variable is the scale of farming (SCA) (Carrer et al., 2017). This factor influences the cost-benefit effect. As bigger farms are often more competitive, have a better cost structure and higher returns, they can bear the investment in new technology (Tey & Brindal, 2012). For smaller farms, even a low price can be a significant barrier to adopt new technology (Rose & Bruce, 2018). On bigger farms, there are much data to collect to make an informed decision in complex farm management. Farmers spend more time in the office to manage their farms and need efficient tools to supply their decisions.

For this reason, farmers that invested a lot in new technology will be more likely to adopt additional new technologies. The adoption can improve their farm efficiency and cover the costs of investments. The technology investments will also be used as a control variable (TI).

The aforementioned hypotheses and impacts are visualized in the conceptual framework in Figure 5.

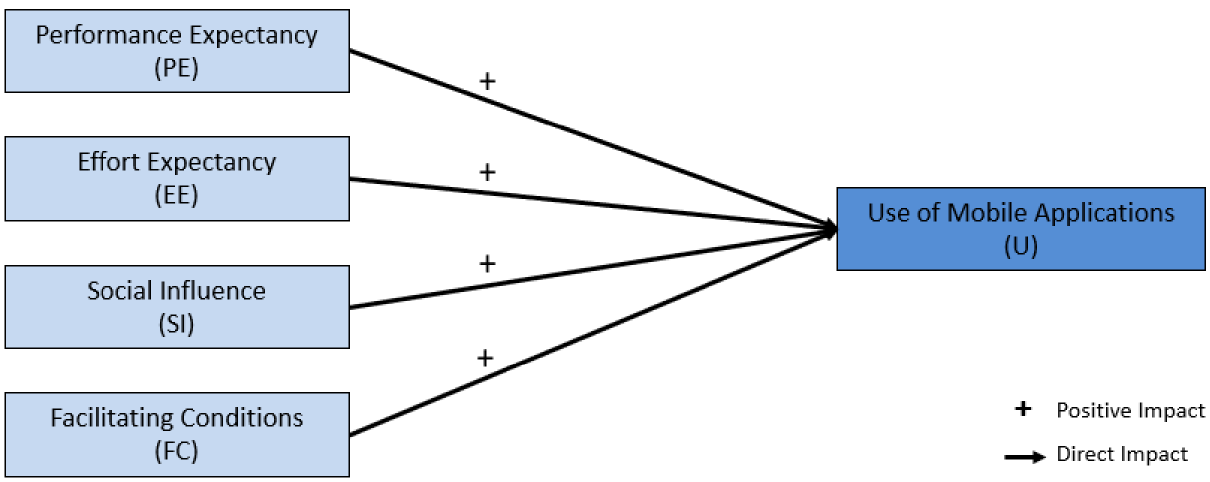

Figure 5: Conceptual Framework - Influencing Factors for the Use of Mobile Applications for Data and Information Management (Modified after Rose et al., 2016; Venkatesh et al., 2003)

3. Materials and Methods

This materials and methods chapter describes the techniques used to answer the research question. In this chapter, the literature research, the creation, and the execution of the questionnaire are explained first. Then the data preparation and evaluation are explained. The validity and reliability of the used methodology and constructs are discussed in the last part.

3.1. Data Collection

Two methods were used to answer the main research question. First, the existing literature was reviewed to identify critical influencing factors for the use of mobile applications. In the second step, a survey was developed, conducted, and evaluated to check the results of the literature search. The two methods used are explained in more detail in the following sections.

3.1.1. Literature Study

For this thesis, desk research was conducted to define relevant factors for the use of mobile applications in agriculture. Since there is a lack of scientific papers on the general use of mobile applications by farmers, research in related fields was conducted. A literature review on general adoption models and on the barriers and enablers of the use of related technologies like FMIS, computers, precision agriculture tools with the keywords: "Adoption, farm management information system, mobile application, agriculture, precision agriculture, and smart farming" was conducted in Scopus and Google Scholar to find and review relevant literature.

The found literature was then sorted for citations and impact factor and filtered for reviews and year of publication to extract the most recent and relevant articles on the topic. From these review articles, a snowball sampling for additional literature was conducted to extract more related articles. A search for general adoption models and influencing factors were also conducted. A search on the agricultural structure in Germany was conducted to define the particularities of the research region. Additionally, sector-specific newspapers, magazines, and other knowledge sources were used, since there are only a few scientific articles on this topic.

3.1.2. Survey

For the cross-sectional survey design, an online questionnaire was created with the tool "Umfrage Online" to test the hypotheses and answer the main research question. The advantage of the online survey is that it can be quickly and cost-effectively distributed over a large geographical area (Kumar, 2011).

3.1.3. Questionnaire Design

The online survey was developed based on the development and application of the UTAUT and the resulting questionnaires that have already been tested and validated (Flight, D'Souza, & Allaway, 2011; Hsu, Ray, & Li-Hsieh, 2014; Im, Hong, & Kang, 2011; Peris & Nüttgens, 2011; Venkatesh et al., 2003). Small changes were made to adapt the construct items to the research topic. The survey is tested for functionality and comprehensibility through a pre-test. Besides, the survey is proofread by the three supervisors and checked for ambiguities.

For the core constructs, PE, EE, SI, and FC, various items are formulated regarding the impact of individual characteristics. These statements are evaluated by the farmers concerning the importance of using an application for data and information management on a seven-point Likert scale. On the scale, "1" describes the negative end of the scale, and "7" is the positive end (Hsu et al., 2014; Venkatesh et al., 2003). After the pretest, item PE_1 was split up into two items (PE_1 and PE_3) as the test respondents found it somehow double-barreled. See Table 1 for the item-overview. The full questionnaire is in the appendix.

For the control variables, the respondent is asked to indicate his farming intensity and technology investments in the last five years with a dichotomous yes / no answer (Rose et al., 2016; Venkatesh et al., 2003). Farmers are asked for their age and the scale of farming on a metric scale. Farmers are also asked for their education to control for the impact of this variable. For the farm characteristics, farmers have to state their type of farming, whether they do arable, livestock farming (cattle, pig, poultry) or energy production (Rose et al., 2016). Also, a blank space for other activities is there to cover the diversity of farms. For the size of the farm, the cultivated area in hectare is asked on a metric scale (Rose et al., 2016). All questions had to be answered before the questionnaire could be finished to avoid missing values. If respondents did not answer a question, they were reminded to complete that particular question, so no adjustments needed to be made to missing scores.

Table 1: Overview Constructs, Measures, and Data Analysis

Hypo-thesis	Con-struct	Item	Measure	Categories	Analysis	Scale origin
Dependent Variable						
		U	Nominal scale	1 = Yes; 0 = No	Logistic regression	Venkatesh et al., 2003
Independent Variables						
H1	PE	PE_1 - PE_8	7-Point Likert scale	"1" negative end of the scale; "7" positive end of the scale	Cronbach´s Alpha Logistic regression	Venkatesh et al., 2003; Peris & Nüttgen, 2011; Im et al., 2011
H2	EE	EE_1 - EE_4				
H3	SI	SI_1 - SI_4				
H4	FC	FC_1 - FC_4				
Control variables: Farming Type and Intensity						
		TI	Nominal scale	1 = Yes; 0 = No	Logistic regression	
		FI	Nominal scale	1 = Yes; 0 = No	Logistic regression	
		TF_1 (arable) TF_2 (cattle) TF_3 (pig) TF_4 (poultry) TF_5 (energy production) TF_6 (others)	Nominal scale	1 = Yes; 0 = No	Logistic regression	Rose et al. 2016
Control variables: Demographics						
		EDU	Nominal scale	1. experience 2. apprenticeship 3. agricultural college 4. Bachelor 5. Master / Diploma 6. others	Descriptive analysis; Logistic regression	
		AGE	Metric, years	16 - 80	Descriptive analysis; Logistic regression	
		SCA	Metric, ha	min. 5	Descriptive analysis; Logistic regression	

3.1.4. Execution of the Survey

Interest groups and regional agricultural offices were contacted to spread the survey. The use of their networks and should obtain a more representative sample of the region. Due to privacy reasons (new DSGVO in Germany) all institutions regretted to spread the survey. For this reason, the survey was spread via social media. Regional farming groups on Facebook were contacted to spread the link to this survey. At the same time, a snowball principle, also called convenience sampling, was used to distribute the survey via WhatsApp. Based on the researcher's network, the link to the questionnaire was spread over the region. The survey participants were able to disseminate the survey to colleagues further. At a minimum, 30 respondents are needed to evaluate the survey statistically (Stutely, 2014). For validity reasons and to generalize the results, however, a significantly higher response rate is attempted (Stutely, 2014). The questionnaire was kept as short as possible to achieve this goal (Kumar, 2011). Closed questions were formulated, and response options were given (Kumar, 2011). This reduced the possibility of incorrect entries from the survey participants.

3.2. Data Analysis

Data analysis is used to find out results from the collected data of the sample. Statistical methods are used to determine the quality of the data to draw conclusions not only for the sample but also for the total population from which the sample originates (Beech, 2015; Kumar, 2011).

3.2.1. Tools and Methods

The data analysis was carried out by exporting the dataset and evaluating it with SPSS v 26 (Statistical Package for the Social Sciences) for the descriptive-, the reliability- and validity analysis, and logistic regression as the dependent variable is dichotomous (Field, 2018).

3.2.2. Preparation and Analysis of Data

The survey was started by 122 participants (1). Eighty-nine of these participants answered the survey thoroughly. Most of the other 33 participants answered less than 50 percent of the questionnaire so that their answers were not taken into account (2). Of the 89 complete questionnaires, 11 were from outside the survey region and therefore dropped (3). One participant did not meet the minimum requirement of five hectares of agricultural land and was also not included in the evaluation (4). One participant, who solely was an agricultural service provider, was also dropped (5).

Thus, the sample for the first reliability check and logistic regression consists of 76 participants. The reliability analysis showed that all constructs and items except FC_3 and FC_4 of the FC-construct were reliable (Field, 2018). These two items were dropped for further analysis (6). Then the means of the constructs were calculated (7). The logistic regression and correlation analysis were conducted to get an overview of the Data (8). Due to the high number of dummy variables (13 dummies) in the model, the model collapsed. The full model lacked multicollinearity, as there were many correlations higher than 0.8 between independent variables (Field, 2018). These correlations made a distinction between the impact of single variables impossible. The five dummies for the different educational degrees were merged into one dummy indicating higher agricultural education (more than three years) with a one and lower education (less than three years) with a zero, to reduce the number of dummy variables (Field, 2018). The dummies of the six different farming types were merged into one dummy for sophisticated farms with more than two branches on the farm indicated by a one and two or fewer branches indicated by a zero (Field, 2018). After this transformation of the two control variables, the model showed a higher model fit and did not lack multicollinearity anymore, as indicated by the correlations in Table 15 in the appendix (9).

Table 2: Overview of Data Preparation

Step	Activity	dropped n	remaining n
1	**Gross answers**		**122**
2	Exclusion of not fully answered cases.	33	89
3	Correction of the regional affiliation according to the postal code.	11	78
4	Exclusion of cases, which do not meet the criteria > 5 ha cultivated arable area.	1	77
5	Exclusion of case, which was an agricultural service provider.	1	76
6	Calculation of Cronbach`s Alpha values to check item-construct reliability. The drop of FC_3 and FC_4.		76
7	Calculation of means of the latent constructs.		76
8	Binary logistic regression with correlation analysis.		76
9	Merge of education dummies and FT-dummies. Reduction of dummy variables from 13 to 4.		76
10	Logistic Regression with saving of standardized residuals (z-values) to check data for outliers and correlation analysis.		76
11	Drop of cases with z-value > 1.96 or < - 1.96.	4	72
12	**Net answers / final dataset for the evaluation**	**50**	**72**
13	Recalculation of Cronbach`s Alpha values to check item-construct reliability of the final dataset.		72
14	Binary logistic regression of the final dataset.		72
15	Correlation analysis of the latent constructs.		72

The logistic regression was conducted, and standardized residual terms were calculated and saved to extract outliers in the dataset (10). Cases with standardized residuals (z-values) > 1.96 or < - 1.96 were dropped as these values are more than two standard deviations away from the mean of the sample (Field, 2018). Four cases did not meet this criterium and were dropped (11). The final dataset consists of 72 cases (12). In the next step, Cronbach´s Alpha values for the final data set were calculated to check for reliability (13). Then a logistic regression analysis was conducted to extract relationships and correlations between the latent constructs and the use of smartphone applications (14). In the end, a correlation analysis of the latent constructs is conducted to determine whether the constructs measure distinct factors of application use (15). Table 2 gives an overview of the data preparation and reduction of cases.

The dataset was analyzed using a binary logistic regression model. The following paragraph explains the model design. The basic logistic regression function used is as follows:

$$P\ (y = 1) = \frac{1}{1 + e^{-z}}$$

P (y = 1) = Probability, that y = 1 (= use of mobile applications)

e = Basis of the natural logarithm, Euler's number

z = Logit (linear regression model of the independent variables)

The logit of the regression model of this research consists of the means of latent constructs and the independent variables controlled for as well as an error term. If the logit is inserted into the basic logistic function, this results in the used regression model (UZH, n.d.):

$$P\ (y = 1) = \frac{1}{1 + e^{-(ß0 + ß1 * PE + ß2 * EE + ß3 * SI + ß4 * FC + ß5 * SCA + ß6 * AGE + ß7 * EDU_{high} + ß8 * FT_{high} + ß9 * TI + ß10 * FI + e)}}$$

Description of Data

The average age of the survey participants is 29.5 years, with a width of 18 to 61 years. The average cultivated area is 79.27 ha per farm. The smallest farm cultivates 10 ha, the largest farm in the sample cultivates 400 ha. Sixty-one participants or 84.7 percent come from the Münsterland region and 15.3 percent or 11 from the Weser-Ems region. Of the participants, the majority had a degree from a higher agricultural school, 27 participants, or 37.5 percent. Seventeen participants or 23.6 percent had a first academic degree (Bachelor). A further three participants or 4.2 percent had a master's degree or diploma. The persons whose knowledge is based on practical experience make up ten participants or 13.9 percent of the sample. Completed vocational training is currently the highest qualification of 15 participants or 20.8 percent.

On 91.7 percent of the farms, arable farming was carried out by the farmers themselves. Pigs are kept on 55.6 percent of holdings and cattle on 48.6 percent. 36.1 percent of the farms are active in energy production, and 15.3 percent keep poultry. Five farms or 6.9 percent of the sample manage other branches of farming, such as horse or sheep farming, direct marketing, or agricultural services.

Of the sample participants, 8.3 percent or six participants operate only one branch of business. Thirty-one holdings or 43.1 percent manage two branches. 36.1 percent or 26 holdings managed three branches, and 11.1 percent or eight farms comprise four branches on their holdings. One farm manages five branches. These high numbers of branches per farm indicate a high degree of mixed farms, which is typical for the research region. Three-quarters (75.0 percent) of the survey respondents indicated that they run their business in an intensive form, and one-quarter (25.0 percent) rated the business as extensively run.

76.4 percent of respondents stated that they use smartphone applications for data and information management in their operations (dependent variable). At the same time, however, only 36.1 percent of participants stated that their farm had invested in smart applications and networkable technologies or machines and control software over the past five years. Most of the applications used on the farm are not directly connected with farm equipment for data gathering and exchange.

Table 3: Overview of Sample Characteristics

Characteristic	Average	Width
Age (years)	29.50	18 to 61
Scale (ha)	79.29	10 to 400
	n (of Sample)	Percent (of Sample)
Dependent Variable Use of Smartphone Application		
Yes (use)	55	76.4
No (use)	17	23.6
Regional Affiliation		
Weser-Ems	11	15.3
Münsterland	61	84.7
Education		
Practical experience	10	13.9
Vocational training	15	20.8
Higher agricultural school	27	37.5
Bachelor degree	17	23.6
Master degree	3	4.2
Farming Type		
Arable farming	66	91.7
Cattle farming	35	48.6
Pig farming	40	55.6
Poultry	11	15.3
Energy production	26	36.1
Others (horses, sheep, direct sale, service provider)	5	6.9
Sum of Branches Managed on Farm		
One branch	6	8.3
Two branches	31	43.1
Three branches	26	36.1
Four branches	8	11.1
Five branches	1	1.4
Six branches	0	0
Farming Intensity		
Intensive	54	75.0
Extensive	18	25.0
Technology Investments in the Past Five Years		
Yes (invested)	26	36.1
No (investments)	46	63.9

So, the participants of the survey are much younger than the average farmer in the region and cultivate more hectares than the average farm of the population. They are also highly educated as more than fifty percent have a degree of a higher agricultural school or university. More than three-quarters of them use smartphone applications for data and information management. Table 3 gives an overview of the aforementioned characteristics. An overview of full descriptive statistics and frequencies is shown in Table 8 and Table 9 in the appendix.

3.3. Reliability and Validity

The research aims to provide accurate results and compelling insights into the research sample and population (Beech, 2015; Kumar, 2011). Therefore, considerable measures are applied to guarantee the internal reliability of the constructs used and the content and construct validity. The measures are explained in the following paragraphs.

3.3.1. Reliability

Reliability describes the robustness and consistency of the results (Kumar, 2011). It is a measure that describes the reproducibility of the results under the same conditions. For the robustness of the results, it is essential to carefully document all the steps taken in the research process, from the literature search, questionnaire development, and data gathering to data analysis so that other researchers can conduct the study in the same way (Beech, 2015).

In this study, consistency is analyzed. Consistency describes the extent to which the items that are combined into a latent construct measure the same construct. Cronbach's Alpha determines consistency. Cronbach's Alpha defines the extent to which individual variables describe a particular construct. Alpha-Values ≥ 0.6 are classified as questionable, values ≥ 0.7 are acceptable, and values ≥ 0.8 are good (Field, 2018).

For the three constructs PE, EE, and SI Cronbach´s Alpha values are good or acceptable, as shown in Table 4. All construct items were kept in the analysis, as dropping of single items reduced or only slightly improved the alpha values shown in Table 10 to Table 12 (Column: Cronbach´s Alpha if the item is deleted) in the appendix.

The construct items FC_3 and FC_4 were dropped, and are in brackets in Table 4. They reduced Cronbach´s Alpha significantly. These two items reduce the internal consistency of the latent constructs and measures. If these items are included, Cronbach´s Alpha for the FC construct is 0.650, which is classified as questionable (Field, 2018). Without the two items, Cronbach´s Alpha for the construct is still classified as questionable but close to acceptable shown in Table 13 in the appendix.

Table 4: Reliability Analysis (Cronbach´s Alpha) (SPSS)

Construct	Item	Cronbach´s Alpha
Performance Expectancy	PE_1	0.859
	PE_2	
	PE_3	
	PE_4	
	PE_5	
	PE_6	
	PE_7	
	PE_8	
Effort Expectancy	EE_1	0.891
	EE_2	
	EE_3	
	EE_4	
Social Influence	SI_1	0.792
	SI_2	
	SI_3	
	SI_4	
Facilitating Conditions	FC_1	0.690
	FC_2	
	(FC_3)	
	(FC_4)	

3.3.2. Validity

Validity refers to the degree to which the measurement methods used accurately measure what they should measure (Beech, 2015). A distinction is made between internal and external validity. Internal validity describes the appropriateness of the methods used to answer the research question (Kumar, 2011). External validity describes whether the results can be generalized and applied to the whole population or whether they are useful for answering similar questions in other fields of science (Beech, 2015). In this study, a validated survey tool (UTAUT) was used to collect farmers' views based on a literature survey. The questions were adapted to the research topic with minimal changes. Three scientific supervisors checked the questionnaire for comprehensibility and consistency. The agreement of the items with the individual constructs was confirmed. In a pretest, the questionnaire was checked for comprehensibility and clarity of the questions in the study group. After the pretest, two items were changed to improve comprehension. For these reasons, the internal validity of this study is high.

The external validity of this study is not high. Due to the small number of participants compared to the total population, the results are only transferable to a limited extent. The convenience sampling did not result in a representative sample (Visser, Kim, Krosnick, & Lavrakas, 2014). A structured sample would be better suited here (Beech, 2015). However, still, the results can be of interest to other fields in the green sector and essential for promoting the use of smartphone applications.

4. Results

The dataset was analyzed using a binary logistic regression model. The following paragraph explains the evaluation of the model concerning its suitability and results of regression analysis.

A Chi-square test is performed (referred to in SPSS as the "omnibus test of model coefficients") to check whether the regression model is significant overall. This test checks whether the model makes an overall explanatory contribution (Field, 2018; UZH, n.d.). The omnibus tests of Table 5 show that the model is significant. So, the model has explanatory value and is suitable to describe the data.

Table 5: Omnibus Tests of Model Coefficients (SPSS)

		Chi-square	df	Significance
Step 1	Step	42,945	10	0,000
	Block	42,945	10	0,000
	Model	42,945	10	0,000

The Nagelkerke R-square, in Table 6, underlines the good fit of the model. The Nagelkerke R-square standardizes the Cox and Snell R-square so that it can only have values between zero and one (UZH, n.d.). The higher the R-square value, the better the fit between model and data ("Goodness of fit") (Field, 2018; UZH, n.d.). The research model has an R-square of 0.676, which states that the model explains 67.6 percent of the variance in data.

Table 6: Model Summary (SPSS)

Step	-2 Log likelihood	Cox & Snell R-Square	Nagelkerke R-Square
1	35,759[a]	0,449	0,676
a. Estimation terminated at iteration number 8 because parameter estimates changed by less than 0,001.			

The logistic regression function calculates probabilities that the dependent variable will take the value one (Field, 2018; UZH, n.d.). These probabilities vary between zero and one (Field, 2018). The classification table shows the percentages of correctly predicted outcomes. In total, 93.1 percent of individuals were classified by the model according to their actual response. Of those who use smartphone applications, 53 out of a total of 55 (53 + 2) were correctly predicted. These numbers correspond to 96.4 percent of correct forecasts. Of those who do not use smartphone applications, 14 out of a total of 17 (14 + 3) were correctly predicted. These correspond to 82.4 percent of correct forecasts, as shownTable 7 in Table 7.

Table 7: Classification Table (SPSS)

Observed			Predicted		
			U_1		Percentage Correct
			0	1	
Step 1 [a]	U_1	0	14	3	82,4
		1	2	53	96,4
	Overall Percentage				93,1

a. The cut value is 0,500

Binary logistic regression analysis shows that the model as a whole (Chi-square = 42.945, $p = 0.000$, $n = 71$, $df = 10$) is significant. In Figure 6, the variable coefficients are presented. It shows that the PE- and SI-constructs are significant on $p = 0.1$ level, and the FC-construct, reduced for the items FC_3 and FC_4, is significant at $p = 0.05$ level. The EE-construct is not significant.

Several of the control variables indicate significant impacts at $p = 0.05$ level (scale, a high number of farming types, and technology investments). The Education of participants is significant at $p = 0.1$ level. Age and farming intensity are not significant as shown in Table 14 in the appendix.

Three variables are particularly crucial for the evaluation of the distinct influences in the model. Firstly, the sign of the regression coefficient B, since this expresses the direction of action and thus the correspondence or opposite with the direction of action of the hypotheses (UZH, n.d.). Second, the significance level because this expresses the level at which the relationships can be regarded as confirmed (Field, 2018; UZH, n.d.). However, the level at which a factor is considered confirmed must be determined beforehand and depends on the research question (Beech, 2015; Kumar, 2011). In this paper, the significance levels of $p = 0.05$ and $p = 0.1$ are adopted since they are common in science (Beech, 2015; Field, 2018). The third factor is the odds ratio Exp (B). This ratio gives information about the change of the probability of the occurrence of a specific state (dependent variable [use of smartphone application] = 1) by increasing the underlying coefficient by one unit (UZH, n.d.).

An odds ratio Exp (B) = 1 indicates the same probability of an event occurring. The ratio Exp (B) < 1 indicates that the probability of an event occurring is lower with the increase of the independent variable (IV) by one unit than the probability of occurring at the original value of the IV. An odds ratio Exp (B) > 1 indicates that the probability of an event occurring is higher with the increase of the IV by one unit than at the original value of the IV. (UZH, n.d.) The key results of the logistic regression are shown in Figure 6. In the next chapter, the influences of the latent constructs on the dependent variable (use of mobile applications) shown in Figure 6 are analyzed and explained. The full model with additional tables is shown in Table 14 in the appendix.

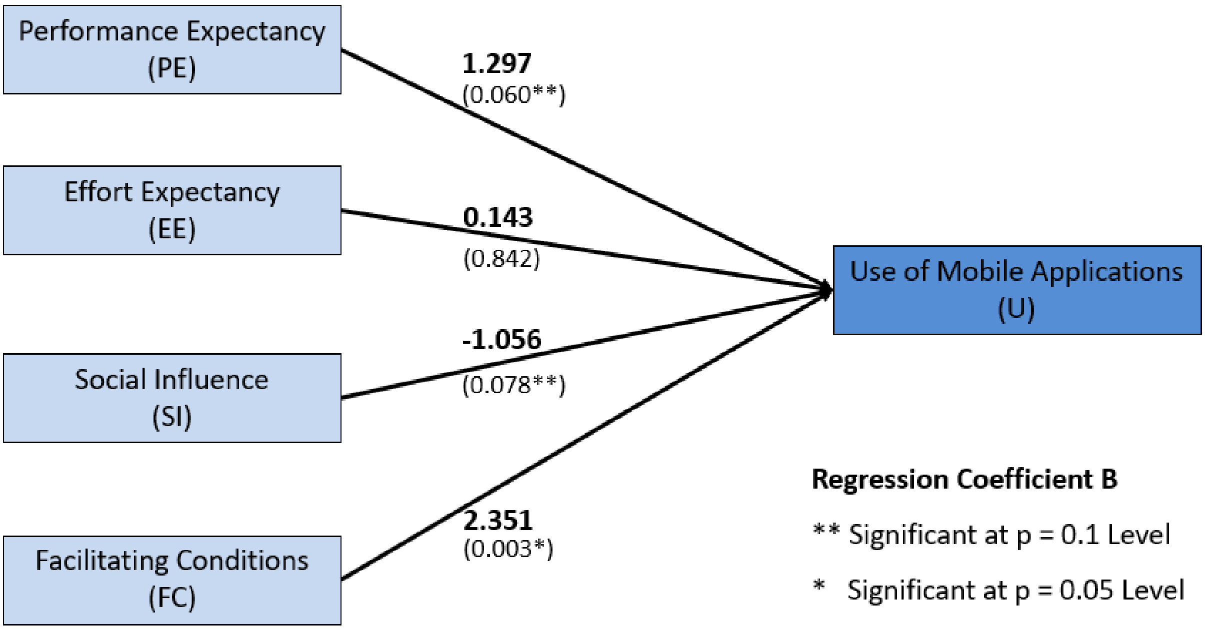

Figure 6: Key Results of the Logistic Regression Analysis

4.1. Performance Expectancy

H1: *High-Performance Expectancy has a positive impact on the use of smartphone applications for data and information management by a farmer.*

PE is considered to be the leading indicator of the use of innovation in the literature (Rose et al., 2016; Venkatesh et al., 2003). High-Performance Expectations of a new application and superiority over existing solutions foster the use (Rose & Bruce, 2018). The regression coefficient B of 1.297 for PE_MEAN in the model indicates a positive relation between PE and the probability of using a smartphone application. The positive relationship is considered to be significant at p = 0.1 level and thus confirms the hypothesis H1 that a high PE has a positive influence on the use of smartphone applications by farmers. This relationship is underlined by the odds ratio Exp (B) = 3.658 > 1, which describes that the relative probability of using a smartphone application increases by 265.8 percent (3.658 – 1 = 2.658) with a one-unit increase in Performance Expectancy.

4.2. Effort Expectancy

H2: *Low Effort Expectancy about a mobile application has a positive impact on the farmer's actual use of it.*

EE describes the expectations a person has about learning to use new technology (Venkatesh et al., 2003). Thus, lower effort expectations increase the probability of adopting smartphone applications (H2). The regression result cannot confirm the relation as it is not significant. The regression coefficient B indicates a positive relationship between the EE and the use of smartphone applications. The questionnaire items for EE have been positively formulated, thus higher scores on the EE_items indicate a lower Effort Expectancy. Therefore, the relationship of the dependent variable use and the EE-construct is in line with the cause-effect relationship of the hypothesis. The odds ratio Exp (B) = 1.153 > 1 indicates that the probability of farmers actual use of smartphone application increase by 15.3 percent (1.153 – 1 = 0.153) with a one-unit increase of the EE-construct and thus a decrease in the expected effort to learn the use of the new technology.

4.3. Social Influence

H3: *The Social Influence surrounding a farmer has a positive impact on the use of mobile applications.*

SI is described as "the degree to which an individual perceives that important others believe he or she should use the system" (Venkatesh et al., 2003). Social Influence is proven to have a significant impact on the use in mandatory context. In contrast, in a voluntary context, it has no significant impact but affects the perception of technology. It fosters internalization and identification with the new technology (Venkatesh et al., 2003). In this research, Social Influence is proven significant at $p = 0.1$ level. The results indicate that the relation between SI and the use of smartphone applications is negative, shown by the negative sign of regression coefficient B of the SI_MEAN. Higher SI would thus decrease the probability of using smartphone applications by 65.2 percent (0.348 – 1 = - 0.652) indicated by the odds ratio Exp (B) = 0.348 < 1.

The H3 hypothesis that the Social Influence surrounding a farmer has a positive impact on the use of mobile applications must be rejected.

4.4. Facilitating Conditions

H4: *The Facilitating Conditions of a mobile application have a significant impact on a farmer's actual use of it.*

There are some basic requirements for the use of smartphone applications. Owning a smartphone and a sufficiently fast internet connection to mobile or stationary networks are essential (Rose & Bruce, 2018). The necessary knowledge for the use of the software must also be available to increase the probability of the farmer using smartphone applications (Rose et al., 2016). In this study, the consistency of the application with programs already available on the farm (FC_3), as well as the support service (FC_4), was investigated. However, these two construct items were not reliable and were therefore excluded from the evaluation.

For the remaining two FC items combined in the FC construct, the model shows a significant relationship with the dependent variable at $p = 0.05$ significance level. The regression coefficient B indicates a positive relationship between FC and the use of smartphone applications. This is confirmed by the odds ratio Exp (B) = 10.494 > 1. A one-unit increase in the Facilitating Conditions increases the probability of using a smartphone application by 949.4 percent (10.494 – 1 = 9.494). Thus, the H4 hypothesis is confirmed by the model.

4.5. Control Variables

Many variables, described in the literature, influence the strength and intensity of the latent constructs previously investigated. In this thesis, the influence of these variables on the constructs has been controlled to identify the unique influence of the studied constructs (Field, 2018). The model shows that this approach was useful because the control variables have significant influences on the model.

The influences of scale (SCA), technology investments (TI), and a high number of branches (more than two) managed on a farm (FT_high) are significant at $p = 0.05$ level. The influence of education (EDU_high = more than three years of agricultural education) is proven significant at $p = 0.1$ level. The influences of age and farming intensity are not proven significant in this model. As many of the variables show significant impacts, it was necessary to control for them.

5. Discussion

This work aimed to find out which factors influence the use of smartphone applications for farmers' data and information management. It was analyzed whether Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions influence the use of applications.

The results of this study will be discussed briefly below and compared with the findings of the literature research.

The results of the binary logistic regression analysis clearly show that the aforementioned latent constructs influence the use of smartphone applications by farmers. The used model was proven significant and had a good model fit. Thus, the model is adequate to answer the research question. The influences vary in strength and are not all significant. There are differences between the results and the cause-effect relationships described in the literature. In the following, the results of the individual constructs are explained in more detail.

The adoption rate of smartphone applications of 75 percent is quite high and is not in line with the findings of other literature. Rose et al. (2016) found “continuing low uptake” of FMIS. In their study, application- and paper-based tools were analyzed. The high uptake rate of this research could be due to the self-selection bias of convenience sampling (Olsen, 2008). The link to the survey was spread via mail, social networks, and WhatsApp. For this reason, the probability that individuals who do not own a smartphone and not use mobile applications participated in the survey was unlikely. The people who received the survey through one of the mobile channels are also highly likely to use other mobile applications (Olsen, 2008).

Another factor that can influence the high number of users of mobile applications is the broad definition used in this paper (Beech, 2015). In this research, simple information applications such as weather, price, and newsletter applications were included. They differ significantly from complex, comprehensive data and information management applications that lead to data-based decision making, which were also included. Further research is needed to gain specific knowledge about the peculiarities of simple management applications. Nevertheless, the study provides a general picture of the factors influencing farmers' use of smartphone applications for data and information management. These factors are discussed in more detail below.

5.1. Performance Expectancy

PE is defined as “the degree to which an individual believes that the use of the system will help achieve gains in job performance” (Venkatesh et al., 2003). One item that measures PE is the cost-benefit or overall performance, which is influenced by the factors´ usability and relevance to the user. The app must offer superiority over already existing solutions to foster the use (Rose et al., 2016).

In literature, this construct is regarded as the one with the highest impact on the use of new technology (Rose et al., 2016; Venkatesh et al., 2003). In this study, the cause-effect relation and high impact were confirmed. However, the effect of the Facilitating Conditions was bigger than the one of application characteristics, which mainly define the Performance Expectancy. These findings can be valid since the Facilitating Conditions are a necessary condition for the use of an application.

If a farmer wants to use an advantageous mobile application, he can only do so if he also has the necessary equipment. The equipment comprises a smartphone or tablet as well as a good mobile internet connection or WLAN on the farm. In her qualitative study Rose et al. (2016) prove this connection. One of the respondents stated that he does not own a smartphone and, therefore, cannot use FMIS even if he wanted to.

5.2. Effort Expectancy

Venkatesh et al. 2003 define EE as “the degree of ease associated with using the system.” Low Effort Expectancy increases the probability of using new technology. Familiarity with similar technologies, IT education, and experience foster the adoption of new technologies (Rose et al., 2016; Rose & Bruce, 2018). The farmer's habits are of great importance because he must be open to new technologies and adapt his habits to the new application. If the effort of adaptation is not too high, the use is more likely (Rose et al., 2016).

In this study, a positive relationship between the low Effort Expectancy and increasing probability of use was found, which is in line with the literature (Rose et al., 2016; Rose & Bruce, 2018; Venkatesh et al., 2003). However, this relation was not significant and can thus not be generalized for the research population.

One reason for insignificance could be the complexity of the application. Very sophisticated applications with many fields of use need more time to be learned. On the other hand, they offer a broader set of possibilities to reduce the time for daily farming operations compared to single solution applications (Eichler Inwood & Dale, 2019; Fountas et al., 2015; Ugochukwu & Phillips, 2018; Wolfert et al., 2017). The farmer must be able to adjust the application to his particular farm purposes (Fountas et al., 2015). So, the Effort Expectancy to implement the application will be high but can offer excellent performance advantages (PE). That some factors can compensate for others is also confirmed by literature (Rose et al., 2016). It is the task of the application providers to develop applications that are easy to understand. Additionally, the applications must offer a wide range of comprehensive solutions and can be adapted by farmers to the specific needs of the farm.

5.3. Social Influence

This research found that Social Influence has a negative relationship with the use of smartphone applications by farmers. The negative relation was proven significant at the p = 0.1 level and is a surprising result that is not in line with existing literature. Venkatesh et al. (2003) defined the Social Influence as "the degree to which an individual perceives that important others believe he or she should use the system" (Venkatesh et al., 2003). In their study, the influence was only proven significant for forced situations but not for voluntary ones (Venkatesh et al., 2003). Nevertheless, the study found a positive correlation for both situations, suggesting that the expectations of others build up social pressure that has a positive effect on the willingness to use (Flight, D'Souza, & Allaway, 2011; Venkatesh et al., 2003). Rose et al. (2016) found in their study for voluntary use that peer recommendation and trust, as well as relations between farmers and farmer-advisor compatibility, have a positive impact on the uptake and use of DST.

However, the results of this study suggest the opposite. For farmers, social pressure seems to have the opposite effect and builds up a blockade attitude. This phenomenon should be investigated in more detail in further studies.

5.4. Facilitating Conditions

FC is defined as "the degree to which the individual believes that organizational and technical infrastructure is available to support the use of the system" (Venkatesh et al., 2003). In their general study on adoption intention and use, Venkatesh et al. (2003) found that FC have a significant impact on the actual use of new technologies. This relation was also confirmed by Rose et al. (2016). They found that a mismatch between the workflow of the farmer and the tool, as well as poor mobile internet access, can prevent the use of new technologies. Poor compatibility with existing systems on-farm can also prevent the use of new technologies by farmers. A good internet connection is an essential condition for the use of applications (Schlee, 2014).

These literature findings are confirmed by this study as the impact of the Facilitating Conditions is the highest and significant at p = 0.05 level. The research showed that not only the existence of physical resources like a mobile device or internet access are necessary conditions for the use but also highlight the importance of knowledge as a mental resource. The ability of the farmer to use software highly depends on his IT-education and knowledge. The farm must allow for the use of applications, e.g., possess the necessary resources. New machinery with sensors and interfaces can foster the use of smart applications by farmers, as this can reduce his workload (Wolfert et al., 2017).

5.5. Limitations of the Research

Every investigation has its limits. In this study, the sample was problematic in particular. After rejections by associations, magazines, and regional offices, a snowball system was used to spread the survey. This method, also called convenience sampling, has the disadvantage that the representativeness of the sample for the study population is not guaranteed (Olsen, 2008). In this study, the sample was, on average, much younger and better educated than the study group. Besides, the farmers managed larger farms than the regional average. For future studies, a stratified sample should be composed to ensure representativeness (Beech, 2015; Kumar, 2011; Visser et al., 2014). Also, self-selection bias may have occurred, as the survey was spread over social networks and mobile applications and was therefore not accessible to persons in the study group who did not use these media (Olsen, 2008).

Another problem was the time required for the survey. Although the survey was as short as possible and mainly with closed questions, many farmers did not carry it out to the end. This issue makes clear that future surveys will have to be shorter or conducted as a personal interview on-site to reduce the proportion of incomplete questionnaires (Beech, 2015; Kumar, 2011; Visser et al., 2014).

An additional limitation of this study was the broad definition of the dependent variable "use of smartphone applications". Both pure information systems and ambitious management applications were covered. A more precise subdivision and a more in-depth analysis of the influencing factors would make sense here.

6. Conclusion

This study aimed to find influencing factors for the use of smartphone applications for farmers' data and information management. In general, it can be said that many different factors are influencing the use of new technologies. The model of the unified theory of acceptance and use of technology (UTAUT) by Venkatesh et al. (2003) summarizes many of these individual factors in the four latent constructs PE, EE, SI, and FC. In this study, the model was applied to the use of smartphone applications for farmers' data and information management to answer the main research question. The items of the latent constructs were adapted to the specific characteristics of farmers and the use of smartphone applications. A binary logistic regression analysis was used to analyze the influence of each construct. It became clear that the construct of the enabling conditions has the most considerable influence on usage. The presence of specific resources like smartphone, internet connection, and knowledge are an essential condition for the use of mobile applications. The performance expectation of the user follows this construct. The new application must be superior to other products and lead to a simplification of activities. Positive performance expectations increase the probability of the actual use of the application. Effort expectations also influence the adoption of new technologies. If the effort required to learn new technology is estimated to be low, the probability of its use increases. The more familiar the farmer is with the applications, the lower the expected effort.

The influence of the SI construct was surprising. In the literature, positive correlations between the user's assessment of the expectations of others and the adoption of new technology were predominantly reported. According to the literature, social desirability has a positive influence on actual use, both in a voluntary and a forced use context.

In contrast, this study found a negative correlation between the influence of the social environment and the use of smartphone applications. It suggests the assumption of a blockade attitude due to high social pressure. However, this must be investigated in greater depth by further scientific investigations.

For this study, a broad definition of smartphone applications was used. This definition included both pure information systems and ambitious management applications. In future investigations, a specified definition should be used to obtain more precise results and starting points for the promotion of mobile applications used for data and information management by farmers.

Especially from farmers, it is difficult to obtain a meaningful sample. Many farmers are sole proprietors and have to cope with a very high workload. The sample collected in this study cannot be considered representative. Thus, the transfer of the results to the study population can be critically questioned.

All in all, it can be concluded that the main influencing factors fall into the categories of performance expectations and enabling conditions. Superiority over existing systems and the availability of the necessary resources form the basis for the adoption of farmers' smartphone applications for data and information management.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I., & Fishbein, M. (1977). Attitude-behavior relations: A theoretical analysis and review of empirical research. *Psychological Bulletin*, *84*(5), 888–918. https://doi.org/10.1037/0033-2909.84.5.888

Balmann, A., & Schaft, F. (2008). Future economic challenges in agricultural production: Structural change in the face of changing markets, policies and technologies [in German]. *Arch. Tierz.* (Dummerstorf 51), 13–24.

Beech, J. (2015). *Doing your business research project*. Los Angeles, Calif.: Sage Publ. https://doi.org/10.4135/9781473910133

Bitcom (2017). Mobile Steuerungszentrale für das Internet of Things. Retrieved from https://www.bitkom.org/Presse/Presseinformation/Mobile-Steuerungszentrale-fuer-das-Internet-of-Things.html

BMEL (2017). Daten und Fakten: Land-, Forst- und Ernährungswirtschaft mit Fischerei Wein und Gartenbau. Retrieved from https://www.bmel.de/SharedDocs/Downloads/Broschueren/DatenundFakten.pdf?__blob=publicationFile

Bonke, V., Fecke, W., Michels, M., & Musshoff, O. (2018). Willingness to pay for smartphone apps facilitating sustainable crop protection. *Agronomy for Sustainable Development*, *38*(5), 1. https://doi.org/10.1007/s13593-018-0532-4

Carrer, M. J., Souza Filho, H. M. de, & Batalha, M. O. (2017). Factors influencing the adoption of Farm Management Information Systems (FMIS) by Brazilian citrus farmers. *Computers and Electronics in Agriculture*, *138*, 11–19. https://doi.org/10.1016/j.compag.2017.04.004

Carrer, M. J., Souza Filho, H. M. de, Batalha, M. O., & Rossi, F. R. (2015). Farm Management Information Systems (FMIS) and technical efficiency: An analysis of citrus farms in Brazil. *Computers and Electronics in Agriculture*, *119*, 105–111. https://doi.org/10.1016/j.compag.2015.10.013

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results.* Massachusetts Institute of Technology.

DBV (2019). Situationsbericht 2018/19: Agrarstruktur. Retrieved from https://www.bauernverband.de/situationsbericht-2018/19

Deimel, M., & Theuvsen, L. (2010). Standortvorteil Nordwestdeutschland? Eine Untersuchung zum Einfluss von Netzwerk- und Clusterstrukturen in der Schweinefleischerzeugung. Retrieved from https://ideas.repec.org/p/zbw/daredp/1004.html

Deloitte (2016). From Agriculture to AgTech: An industry transformed beyond molecules and chemicals. *Deloitte Monitor*. (Issue 8).

Destatis (2019a). Agrarstrukturerhebung 2016: 9 600 land-wirtschaft-liche Betriebe weniger als im Jahr 2013. Retrieved from https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Landwirtschaft-Forstwirtschaft-Fischerei/Landwirtschaftliche-Betriebe/aktuell-landwirtschaftliche-betriebe.html

Destatis (2019b). Landwirtschaftliche Betriebe: Arbeitskräfte Fachserie 3. Retrieved from https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Landwirtschaft-Forstwirtschaft-Fischerei/Landwirtschaftliche-Betriebe/_inhalt.html

Deter, A. (2013). Durchschnittsalter der Landwirte beträgt 53 Jahre. Retrieved from https://www.topagrar.com/management-und-politik/news/durchschnittsalter-der-landwirte-betraegt-53-jahre-9564620.html

Detlor, B. (2010). Information management. *International Journal of Information Management*, *30*(2), 103–108. https://doi.org/10.1016/j.ijinfomgt.2009.12.001

Eichler Inwood, S. E., & Dale, V. H. (2019). State of apps targeting management for sustainability of agricultural landscapes. A review. *Agronomy for Sustainable Development*, *39*(1), 46. https://doi.org/10.1007/s13593-018-0549-8

FAO. (2009b). *Feeding the World in 2050: World Summit on Food Security*. Rome.

FAO (2009a). How to Feed the World in 2050.

Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th edition). Los Angeles, London, New Delhi, Singapore, Washington DC, Melbourne: SAGE.

IT NRW (2017, December 13). *Landwirtschaft in Nordrhein-Westfalen: – Ergebnisse der Agrarstrukturerhebung 2016 –: Pressekonferenz im Pressezentrum des Landtags in Düsseldorf anlässlich der Veröffentlichung des Statistischen Jahrbuchs 2017* [Press release]. Düsseldorf. Retrieved from https://www.it.nrw/sites/default/files/atoms/files/343a_17.pdf

Flight, R. L., D'Souza, G., & Allaway, A. W. (2011). Characteristics-based innovation adoption: scale and model validation. *Journal of Product and Brand Management*. (20/5), 343–355. https://doi.org/10.1108/10610421111157874

Fountas, S., Carli, G., Sørensen, C. G., Tsiropoulos, Z., Cavalaris, C., Vatsanidou, A., Tisserye, B. (2015). Farm management information systems: Current situation and future perspectives. *Computers and Electronics in Agriculture*, *115*, 40–50. https://doi.org/10.1016/j.compag.2015.05.011

Gabler (2018a). Wirtschaftslexikon: Revision von Anwendung vom 19.02.2018 - 13:18. Retrieved from https://wirtschaftslexikon.gabler.de/definition/anwendung-30014/version-253608

Gabler (2018b). Wirtschaftslexikon: Revision von Mobile Business vom 19.02.2018 - 13:18. Retrieved from https://wirtschaftslexikon.gabler.de/definition/mobile-business-53530/version-276612

Gabler (2018d). Wirtschaftslexikon: Revision von Mobile Computing vom 19.02.2018 - 13:18. Retrieved from https://wirtschaftslexikon.gabler.de/definition/mobile-computing-37278/version-260716

Gabler (2018c). Wirtschaftslexikon: Revision von mobile Datenerfassung vom 19.02.2018 - 13:18. Retrieved from https://wirtschaftslexikon.gabler.de/definition/mobile-datenerfassung-39931/version-263328

Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Toulmin, C. (2010). Food security: The challenge of feeding 9 billion people. *Science (New York, N.Y.)*, *327*(5967), 812–818. https://doi.org/10.1126/science.1185383

Hasler, K., Olfs, H.-W., Omta, O., & Bröring, S. (2017). Drivers for the Adoption of Different Eco-Innovation Types in the Fertilizer Sector: A Review. *Sustainability*, *9*(12), 2216. https://doi.org/10.3390/su9122216

Jayaraman, P. P., Yavari, A., Georgakopoulos, D., Morshed, A., & Zaslavsky, A. (2016). Internet of Things Platform for Smart Farming: Experiences and Lessons Learnt. *Sensors (Basel, Switzerland)*, *16*(11). https://doi.org/10.3390/s16111884

Kaloxylos, A., Eigenmann, R., Teye, F., Politopoulou, Z., Wolfert, S., Shrank, C., Kormentzas, G. (2012). Farm management systems and the Future Internet era. *Computers and Electronics in Agriculture*, *89*, 130–144. https://doi.org/10.1016/j.compag.2012.09.002

Köksal, Ö., & Tekinerdogan, B. (2018). Architecture design approach for IoT-based farm management information systems. *Precision Agriculture*, *17*(4), 2347. https://doi.org/10.1007/s11119-018-09624-8

Kumar, R. (2011). *Research Methodology - A step-by-step guide for beginners.*: SAGE Publications. Retrieved from http://www.sociology.kpi.ua/wp-content/uploads/2014/06/Ranjit_Kumar-Research_Methodology_A_Step-by-Step_G.pdf

LSN (2019). Agrarstrukturerhebung (ASE) 2016: Größenstruktur der landwirtschaftlichen Betriebe und Forstbetriebe, Struktur der Bodennutzung, Hauptnutzungs-und Kulturarten Wald und Kurzumtriebsplantagen. Retrieved from https://www.statistik.niedersachsen.de/themenbereiche/landwirtschaft/themenbereich-land--und-forstwirtschaft-fischerei---statistische-berichte-173829.html

Moore, G. C., & Benbasat, I. (1996). Integrating Diffusion of Innovations and Theory of Reasoned Action models to predict utilization of information technology by end-users. In K. Kautz & J. Pries-Heje (Eds.), *IFIP - The International Federation for Information Processing. Diffusion and Adoption of Information Technology: Proceedings of the first IFIP WG 8.6 working conference on the diffusion and adoption of information technology, Oslo, Norway, October 1995* (Vol. 50, pp. 132–146). Boston, MA: Springer. https://doi.org/10.1007/978-0-387-34982-4_10

Olsen, R. (2008). Self-Selection Bias. In P. Lavrakas (Ed.), *Encyclopedia of Survey Research Methods.* 2455 Teller Road, Thousand Oaks California 91320 United States of America: Sage Publications, Inc. https://doi.org/10.4135/9781412963947.n526

Otten, D. (2013). *Eine nachhaltige Entwicklung der intensiven Veredelung in Nordwestdeutschland: betriebliche Herausforderungenund Lösungsansätze derPrimärproduktionin der Region: Dissertation zur Erlangung des Doktorgrades der Fakultät für Agrarwissenschaften der Georg-August-Universität Göttingen*. Göttingen. Retrieved from https://d-nb.info/104487077X/34

Pham, X., & Stack, M. (2018). How data analytics is transforming agriculture. *Business Horizons*, *61*(1), 125–133. https://doi.org/10.1016/j.bushor.2017.09.011

Pivoto, D., Waquil, P. D., Talamini, E., Finocchio, C. P. S., Dalla Corte, V. F., & Vargas Mores, G. de (2018). Scientific development of smart farming technologies and their application in Brazil. *Information Processing in Agriculture*, *5*(1), 21–32. https://doi.org/10.1016/j.inpa.2017.12.002

Ribeiro, I. (2015). World Population Prospects: Key findings and advance tables. *World Population Prospects*, *The 2015 Revision*.

Roberts, R. K., English, B. C., Larson, J. A., Cochran, R. L., Goodman, W. R., Larkin, S. L., Reeves, J. M. (2004). Adoption of Site-Specific Information and Variable-Rate Technologies in Cotton Precision

Farming. *Journal of Agricultural and Applied Economics*, *36*(1), 143–158. https://doi.org/10.1017/S107407080002191X

Rogers, E. M. (1961). Bibliography on the Diffusion of Innovations.

Rose, D. C., & Bruce, T. J. A. (2018). Finding the right connection: What makes a successful decision support system? *Food and Energy Security*, *7*(1), e00123. https://doi.org/10.1002/fes3.123

Rose, D. C., Sutherland, W. J., Parker, C., Lobley, M., Winter, M., Morris, C., Dicks, L. V. (2016). Decision support tools for agriculture: Towards effective design and delivery. *Agricultural systems*, *149*, 165–174. https://doi.org/10.1016/j.agsy.2016.09.009

Schlee, H. (2014). Apps und Smartphones in der Landwirtschaft – Das Büro in der Hosentasche. Retrieved from https://agrarblogger.de/2014/05/27/apps-und-smartphones-in-der-landwirtschaft-das-buro-in-der-hosentasche/

Sonka, S. (2014). *Big Data and the Ag Sector: More than Lots of Numbers.* https://doi.org/10.22004/AG.ECON.163351

Sørensen, C. G., Fountas, S., Nash, E., Pesonen, L. [L.], Bochtis, D., Pedersen, S. M., Blackmore, S. B. (2010). Conceptual model of a future farm management information system. *Computers and Electronics in Agriculture*, *72*(1), 37–47. https://doi.org/10.1016/j.compag.2010.02.003

Spiller, A., & Schulze, B. (2008). *Zukunftsperspektiven der Fleischwirtschaft: Verbraucher, Märkte, Geschäftsbeziehungen*. Göttingen: Niedersächsische Staats- und Universitätsbibliothek; Univ.-Verl. Göttingen. Retrieved from http://resolver.sub.uni-goettingen.de/purl?isbn-978-3-940344-13-7

Statistisches Bundesamt (2014). Land und Forstwirtschaft, Fischerei. Arbeitskräfte, Agrarstrukturerhebung 2013., *Fachserie 3, Reihe 2.1.8*.

Stutely, M. (2014). *The Economist numbers guide: The essentials of business numeracy* (Sixth edition). *Economist books*. New York, NY: PublicAffairs.

Szilagyi, R., & Herdon, M. (2006). Impact Factors For Mobile Internet Applications In The Agri-food Sectors. Advance online publication. https://doi.org/10.13031/2013.21882

Tey, Y. S., & Brindal, M. (2012). Factors influencing the adoption of precision agricultural technologies: a review for policy implications. *Precision Agriculture*, *13*(6), 713–730. https://doi.org/10.1007/s11119-012-9273-6

Tummers, J., Kassahun, A., & Tekinerdogan, B. (2019). Obstacles and features of Farm Management Information Systems: A systematic literature review. *Computers and Electronics in Agriculture*, *157*, 189–204. https://doi.org/10.1016/j.compag.2018.12.044

Ugochukwu, A. I., & Phillips, P. W. B. (2018). Technology Adoption by Agricultural Producers: A Review of the Literature. In N. Kalaitzandonakes, E. G. Carayannis, E. Grigoroudis, & S. Rozakis (Eds.), *Innovation, Technology, and Knowledge Management. From Agriscience to Agribusiness* (Vol. 13, pp. 361–377). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-67958-7_17

UZH (n.d.). Methodenberatung: Logistische Regressionsanalyse. Retrieved from https://www.methodenberatung.uzh.ch/de/datenanalyse_spss/zusammenhaenge/lreg.html

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27(3)*, 425–478. Retrieved from http://www.vvenkatesh.com/wp-content/uploads/2015/11/2003(3)_MISQ_Venkatesh_etal.pdf

Verdouw, C. (2016). Internet of Things in agriculture. *CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources*, *11*(035). https://doi.org/10.1079/PAVSNNR201611035

Visser, P. S., Kim, N., Krosnick, J. A., & Lavrakas, P. J. (2014). Survey Research. In H. T. Reis & C. M. Judd (Eds.), *Handbook of research methods in social and personality psychology.* New York, NY: Cambridge University Press.

WHO (2003). Diet, Nutrition and the Prevention of Chronic Diseases: Report of a Joint WHO/FAO Expert Consultation. *WHO Technical Report Series*. (916). Retrieved from https://apps.who.int/iris/bitstream/handle/10665/42665/WHO_TRS_916.pdf;jsessionid=7C3B53BE0DAD66C8D1F1DC2D206BFAFE?sequence=1

Windhorst, H.-W., & Grabkowsky, B. (2007). Die Bedeutung der Ernährungswirtschaftin Niedersachsen. Retrieved from https://www.researchgate.net/profile/Hans_Windhorst/publication/264869216_Die_Bedeutung_der_Ernahrungswirtschaft_in_Niedersachsen/links/53f6e3dd0cf2fceacc74d99c/Die-Bedeutung-der-Ernaehrungswirtschaft-in-Niedersachsen.pdf

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big Data in Smart Farming – A review. *Agricultural systems*, *153*, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023

Appendices

Online Questionnaire

The following tables show the questionnaire items for the different constructs.
First, an introductory paragraph explains the aim of the research to the survey participants:
Following introduction was used:

My name is Johannes Krümpel. I am conducting this survey on mobile applications for data and information management of farmers as part of my master thesis at the universities of Bonn and Wageningen (NL). The survey is entirely anonymous. The first two digits of the postcode are captured to narrow down the survey area. The survey relates to the northwest of the federal state of North Rhine Westphalia, known as "Münsterland"-region and the south-west of Lower Saxony known as "Weser-Ems"-region.

The survey takes about 5 minutes and is divided into three sections. The first section is about you as a person.

In the second part, the usage of applications and their characteristics are investigated. In the third section, questions on your farm are asked.

After successful participation, you can leave your e-mail address to participate in the PROFIT GAME. Two 50 € AMAZON GIFTS will be raffled among all participants.

Thanks for your participation!

Part 1: Questions to the Farmer´s Person

1. **How old are you?**

____

2. **What is your highest degree of education for farming?**

___Practical experience
___Apprenticeship as a farmer
___Agricultural College / Technician
___Bachelor degree
___Master degree / Diploma
___Others: _________________________

3. **Name the first two digits of your postal code.**

____

4. **Do you use a mobile application for data and information management at your farm?**

Yes/No

If yes, which ones?

1.__________________________2.__________________________3.__________________________

5. **Do you use mobile farm management information systems on your farm?**

Yes/No

If yes, which ones?

1.__________________________2.__________________________3.__________________________

Part 2: Examines Farmer´s Evaluation of the Items.

The Survey participants were asked to evaluate the following statements on a 7-point Likert scale, where "1" represents the negative end of the scale, and "7" represents the positive end.

Table PE: Adjusted UTAUT Construct-Items Performance Expectancy (PE)

PE_1	I find mobile applications for data and information management useful to maintain contacts in my network.
PE_2	I find mobile data and information management applications useful for networking in my business.
PE_3	I find mobile applications for data and information management useful for exchanging data within my farm (Workers and farm equipment).
PE_4	I find mobile data and information management applications useful for exchanging data with other companies (feed, contractors, consultants) in my company's network.
PE_5	I find mobile applications for data and information management useful to acquire data faster.
PE_6	When I use mobile applications for data and information management, I can exchange data with other companies more quickly.
PE_7	When I use mobile applications for data and information management, I get faster support from experts in my network.
PE_8	Using mobile applications for data and information management helps me overall in my agricultural activity and increases my productivity.

Table EE: Adjusted UTAUT Construct-Items Effort Expectancy (EE)

EE_1	For me, working with mobile applications for data and information management is clear and understandable.
EE_2	I find mobile applications for data and information management easy to use.
EE_3	It is easy for me to learn how to use mobile applications for data and information management.
EE_4	I feel confident in adjusting mobile applications to my specific needs.

Table SI: Adjusted UTAUT Construct-Items Social Influence (SI)

SI_1	Farmers/Colleagues in my network believe that I should use mobile applications for data and information management.
SI_2	Farmers/Colleagues who are important to me believe that I should use mobile applications for data and information management.
SI_3	The farm allows the use of mobile applications for data and information management.
SI_4	The farm supports the use of mobile applications for data and information management.

Table FC: Adjusted UTAUT Construct-Items Facilitating Conditions (FC)

FC_1	I have the necessary resources, such as a mobile phone/tablet with internet access, to be able to use a mobile application for data and information management.
FC_2	I have the necessary knowledge to use a mobile application for data and information management.
FC_3	The mobile application for data and information management is not comparable to other programs that I use in my daily work.
FC_4	A specific person or group can be reached by phone, e-mail, or in person if there are problems with mobile data and information management applications.

Part 3: Examines the Control Variables (Farm Features)

Table TI: UTAUT Control Variable Technology Investment (TI)

TI	I invested in smart farming equipment in the past five years

Table FI: UTAUT Control Variable Farming Intensity (FI)

FI	I manage my farm in capital and time-intensive way.

Table FT: UTAUT Control Variable Type of Farming (FT)

FT	Farming type, with different categories: 1: arable 2: cattle 3: pig

	4: poultry 5: energy production 6: others

At the end of the questionnaire, the following text was presented:

You have answered all the questions. Thank you very much for your participation!

You can now leave your email address to enter the competition.

____

The email address is only used for the competition. The address will be stored completely separated from all other data. It will only be used to determine the winners. Immediately after the draw, all email addresses will be irrevocably deleted.

Leave a message here if you have any suggestions or comments about the survey.

____

____

If you would like to receive the results of the survey, please send me an email to the following address: Johannes.Krumpel@wur.nl

Please tick the Button "Done" at the end of the page to finish the survey.

Yours sincerely Johannes Krümpel

The questionnaire was translated into German and pretested by two participants.

Additional Tables

Table 8: Descriptive Statistics of the Sample (SPSS)

	N	Minimum	Maximum	Mean	Std. Deviation
SCA	72	10,00	400,00	79,27	63,77
AGE	72	18,00	61,00	29,50	10,44
PE_MEAN	72	1,00	7,00	4,74	1,13
EE_MEAN	72	1,00	6,75	4,77	1,24
SI_MEAN	72	1,00	6,75	4,57	1,22
FC_MEANr	72	1,00	7,00	5,62	1,41
Valid N (listwise)	72				

Table 9: Frequency Table of the Sample (SPSS)

USE (Dependent Variable)		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0 (No)	17	23,6	23,6	23,6
	1 (Yes)	55	76,4	76,4	100,0
	Total	72	100,0	100,0	
Postal Code (PLZ)		**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	26 (Weser-Ems)	3	4,2	4,2	4,2
	48 (Münsterland)	61	84,7	84,7	88,9
	49 (Weser-Ems)	8	11,1	11,1	100,0
	Total	72	100,0	100,0	
Education (EDU)		**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	Practical experience	10	13,9	13,9	13,9
	Apprenticeship	15	20,8	20,8	34,7
	Higher agricultural school	27	37,5	37,5	72,2
	Bachelor	17	23,6	23,6	95,8
	Master/Diploma	3	4,2	4,2	100,0
	Total	72	100,0	100,0	
Technology investments		**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	0 (No)	46	63,9	63,9	63,9
	1 (Yes)	26	36,1	36,1	100,0
	Total	72	100,0	100,0	
Farming intensity		**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	0 (extensive)	18	25,0	25,0	25,0
	1 (intensive)	54	75,0	75,0	100,0
	Total	72	100,0	100,0	

TF_Arable farming		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	6	8,3	8,3	8,3
	1	66	91,7	91,7	100,0
	Total	72	100,0	100,0	

FT_Cattle farming		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	37	51,4	51,4	51,4
	1	35	48,6	48,6	100,0
	Total	72	100,0	100,0	

FT_Pig farming		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	32	44,4	44,4	44,4
	1	40	55,6	55,6	100,0
	Total	72	100,0	100,0	

FT_Poultry farming		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	61	84,7	84,7	84,7
	1	11	15,3	15,3	100,0
	Total	72	100,0	100,0	

FT_Energy production		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	46	63,9	63,9	63,9
	1	26	36,1	36,1	100,0
	Total	72	100,0	100,0	

FT_Others		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	67	93,1	93,1	93,1
	1	5	6,9	6,9	100,0
	Total	72	100,0	100,0	

FT_Sum of branches managed on farm		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	one	6	8,3	8,3	8,3
	two	31	43,1	43,1	51,4
	three	26	36,1	36,1	87,5
	four	8	11,1	11,1	98,6
	five	1	1,4	1,4	100,0
	Total	72	100,0	100,0	
Education_high (# years of agricultural education)		**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	0 (less than three years)	25	34,7	34,7	34,7
	1 (more than three years)	47	65,3	65,3	100,0
	Total	72	100,0	100,0	
FT_high (# branches on the farm)		**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	0 (two or less)	37	51,4	51,4	51,4
	1 (more than two)	35	48,6	48,6	100,0
	Total	72	100,0	100,0	

Table 10: Reliability Check: Cronbach´s Alpha of the PE-Construct (SPSS)

		N	%
Cases	Valid	72	100,0
	Excluded[a]	0	0,0
	Total	72	100,0

a. Listwise deletion based on all variables in the procedure.

Cronbach's Alpha	N of Items
0,859	8

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PE_1	33,18	70,460	0,356	0,868
PE_2	32,78	64,091	0,659	0,836
PE_3	33,21	63,548	0,575	0,845
PE_4	33,29	62,604	0,639	0,837
PE_5	32,57	67,009	0,560	0,847
PE_6	33,22	61,725	0,710	0,829
PE_7	33,82	62,347	0,643	0,837
PE_8	33,35	61,272	0,696	0,830

Table 11: Reliability Check: Cronbach´s Alpha of the EE-Construct (SPSS)

Cronbach's Alpha	N of Items
0,891	4

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
EE_1	14,31	12,807	0,845	0,826
EE_2	14,44	13,941	0,826	0,835
EE_3	14,14	14,178	0,774	0,854
EE_4	14,36	16,009	0,606	0,913

Table 12: Reliability Check: Cronbach´s Alpha of the SI-Construct (SPSS)

Cronbach's Alpha	N of Items
0,792	4

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SI_1	13,67	15,070	0,583	0,750
SI_2	13,76	14,521	0,597	0,743
SI_3	13,39	14,297	0,609	0,737
SI_4	13,97	13,577	0,620	0,733

Table 13: Reliability Check: Cronbach´s Alpha of the FC-Construct (SPSS)

1. Cronbach's Alpha	N of Items			
0,650	4			
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
FC_1	14,06	11,124	0,553	0,492
FC_2	14,49	11,042	0,542	0,498
FC_3	15,54	14,280	0,309	0,656
FC_4	15,58	12,782	0,334	0,651
2. Cronbach's Alpha	N of Items			
0,656	3			
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
FC_1	9,71	7,252	0,518	0,491
FC_2	10,14	7,079	0,522	0,483
FC_4	11,24	7,986	0,368	0,690
3. Cronbach's Alpha	N of Items			
0,690	2			
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
FC_1	5,40	2,666	0,527	
FC_2	5,83	2,563	0,527	

1. **Reliability of full item set:**
2. **Reliability of FC-construct with item FC_3 dropped:**
3. **Reliability of FC construct with items FC_3 and FC_4 dropped:**

Table 14: Full Logistic Regression Model (SPSS)

Case Processing Summary			
Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	72	100,0
	Missing Cases	0	0,0
	Total	72	100,0
Unselected Cases		0	0,0
Total		72	100,0
a. If weight is in effect, see classification table for the total number of cases.			

Dependent Variable Encoding	
Original Value	Internal Value
0	0
1	1

Block 0: Beginning Block

Classification Table[a,b]					
Observed			Predicted		
			U_1		Percentage Correct
			0	1	
Step 0	U_1	0	0	17	0,0
		1	0	55	100,0
	Overall Percentage				76,4
a. Constant is included in the model.					
b. The cut value is 0,500					

Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp (B)
Step 0	Constant	1,174	0,277	17,902	1	0,000	3,235

Variables not in the Equation					
			Score	df	Sig.
Step 0	Variables	PE_MEAN	5,578	1	0,018
		EE_MEAN	2,768	1	0,096
		SI_MEAN	1,653	1	0,199
		FC_MEAN	12,683	1	0,000
		SCA	0,327	1	0,567
		AGE	0,853	1	0,356
		EDU_high	0,003	1	0,955
		FT_high	8,541	1	0,003
		TI	3,289	1	0,070
		FI	1,258	1	0,262
	Overall Statistics		28,887	10	0,001

Block 1: Method = Enter

Omnibus Tests of Model Coefficients				
		Chi-square	df	Sig.
Step 1	Step	42,945	10	0,000
	Block	42,945	10	0,000
	Model	42,945	10	0,000

Model Summary			
Step	-2 Log likelihood	Cox & Snell R-Square	Nagelkerke R-Square
1	35,759[a]	0,449	0,676
a. Estimation terminated at iteration number 8 because parameter estimates changed by less than 0,001.			

Classification Table[a]					
Observed			Predicted		
			U_1		Percentage Correct
			0	1	
Step 1	U_1	0	14	3	82,4
		1	2	53	96,4
	Overall Percentage				93,1
a. The cut value is 0,500					

	Variables in the Equation					
Step 1	B	S.E.	Wald	df	Sig.	Exp(B)
PE_MEAN	1,297	0,690	3,533	1	0,060 **	3,658
EE_MEAN	0,143	0,714	0,040	1	0,842	1,153
SI_MEAN	-1,056	0,599	3,109	1	0,078 **	0,348
FC_MEAN	2,351	0,802	8,602	1	0,003 *	10,494
SCA	-0,018	0,009	4,203	1	0,040 *	0,982
AGE	0,106	0,078	1,846	1	0,174	1,112
EDU_high	1,905	1,158	2,706	1	0,100 **	6,721
FT_high	5,885	2,032	8,393	1	0,004 *	359,768
TI	5,131	1,843	7,754	1	0,005 *	169,239
FI	-0,969	1,127	0,740	1	0,390	0,379
Constant	-18,704	7,680	5,932	1	0,015 *	0,000
	* Significant at p = 0.05 level ** Significant at p = 0.1 level					

Table 15: Correlation Table of the Model (SPSS)

Correlation table											
Step_1	FI	TI	FT_high	EDU_high	AGE	SCA	FC_MEAN	SI_MEAN	EE_MEAN	PE_MEAN	Constant
Constant	0,368	-0,529	-0,735	-0,501	-0,815	0,503	-0,674	0,283	-0,390	-0,662	1,000
PE_MEAN	-0,385	0,302	0,479	0,249	0,542	-0,215	0,391	-0,447	0,050	1,000	-0,662
EE_MEAN	0,019	-0,034	0,271	0,176	0,310	-0,322	-0,150	-0,227	1,000	0,050	-0,390
SI_MEAN	0,174	-0,399	-0,497	-0,212	-0,201	0,259	-0,460	1,000	-0,227	-0,447	0,283
FC_MEAN	-0,385	0,733	0,740	0,472	0,442	-0,467	1,000	-0,460	-0,150	0,391	-0,674
SCA	-0,002	-0,652	-0,652	-0,555	-0,239	1,000	-0,467	0,259	-0,322	-0,215	0,503
AGE	-0,447	0,342	0,400	0,135	1,000	-0,239	0,442	-0,201	0,310	0,542	-0,815
EDU_high	-0,051	0,441	0,512	1,000	0,135	-0,555	0,472	-0,212	0,176	0,249	-0,501
FT_high	-0,269	0,654	1,000	0,512	0,400	-0,652	0,740	-0,497	0,271	0,479	-0,735
TI	-0,260	1,000	0,654	0,441	0,342	-0,652	0,733	-0,399	-0,034	0,302	-0,529
FI	1,000	-0,260	-0,269	-0,051	-0,447	-0,002	-0,385	0,174	0,019	-0,385	0,368

Personal declaration

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I hereby affirm that I have prepared the present thesis self-dependently, and without the use of any other tools, than the ones indicated. All parts of the text, having been taken over verbatim or analogously from published or not published scripts, are indicated as such. The thesis hasn't yet been submitted in the same or similar form, or in extracts within the context of another examination.

Paderborn, 20.12.2019

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Student's signature