



# Acceptance of artificial intelligence in German agriculture: an application of the technology acceptance model and the theory of planned behavior

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## Abstract

The use of Artificial Intelligence (AI) in agriculture is expected to yield advantages such as savings in production resources, labor costs, and working hours as well as a reduction in soil compaction. However, the economic and ecological benefits of AI systems for agriculture can only be realized if farmers are willing to use them. This study applies the technology acceptance model (TAM) of Davis (1989) and the theory of planned behavior (TPB) of Ajzen (1991) to investigate which behavioral factors are influencing the acceptance of AI in agriculture. The composite model is extended by two additional factors, expectation of property rights over business data and personal innovativeness. A structural equation analysis is used to determine the importance of factors influencing the acceptance of AI systems in agriculture. For this purpose, 84 farmers were surveyed with a letter or an online questionnaire. Results show that the perceived behavioral control has the greatest influence on acceptance, followed by farmers' personal attitude towards AI systems in agriculture. The modelled relationships explain 59% of the total variance in acceptance. Several options and implications on how to increase the acceptance of AI systems in agriculture are discussed.

**Keywords** Artificial intelligence · Structural equation model · Survey · Technology acceptance model · Theory of planned behavior

## Introduction

Market research companies and industry associations such as the digital association Bitkom and the German Farmers' Association create the impression that German agriculture is modern, progressive, and innovative. German agriculture is portrayed as a driver of digitalization in rural areas, and farmers as “pioneers of digitalization” (Bitkom and German Farmers' Association, 2019). In its annual report, the German Rentenbank (2018), an agricultural bank, attributes a leading role in digitalization to the agricultural sector. A

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joint survey project of the three institutions mentioned above reveals that 82% of the 500 farmers surveyed report using smart farming technologies (Bitkom, 2020). The company, PricewaterhouseCoopers (PwC), states that German agriculture took a leading role in the adaptation of digital technologies years ago and has maintained this role to date (Bovensiepen et al., 2016). At the same time, the agricultural sector is facing challenges such as the increasing importance of natural resource conservation which demands a more economical use of production resources, such as water, fertilizers, pesticides, and human labor (Finger et al., 2019; Lowenberg-DeBoer et al., 2020). In addition, agriculture is important for ensuring food security for the growing world population which is predicted to reach ten billion people in 2050 (Schrijver et al., 2016). Additionally, many production decisions have to increasingly be made under uncertainty due to weather changes, different local soil conditions, and plant diseases.

In the agricultural machinery industry, various data-driven technology developments are emerging as a possible response to these environmental and socio-demographic challenges (Antle, 2019; Aubert et al., 2012; Blasch et al., 2020; Wolfert et al., 2017). Precision agriculture, a management strategy that aims to improve the resource efficiency, productivity, quality, profitability, and sustainability of agricultural production by using spatial and individual data in addition to other information (International Society of Precision Agriculture (ISPA), 2018), was introduced in the early 1980s (Mulla & Khosla, 2016). It can be noticed that, recently, precision agriculture is further evolving and the term smart farming is gaining attention. By using smart farming applications, e.g., AI driven technologies, production inputs, such as water, plant protection products, herbicides, and human labor, can be managed even more intelligently which positively affects soil fertility, and increases productivity and farmers' monetary resources (Kakani et al., 2020; Partel et al., 2019; Talaviya et al., 2020; Walter et al., 2017). Thus, AI transforms precision agriculture into a more intelligent management system that focuses even more precisely on the individual characteristics of plants, soil types, and animals (Jha et al., 2019). Regarding the term intelligence, no standard definition exists. The corresponding literature provides different definitions, all of which describe a relatively similar subject in different words. Legg and Hutter (2007) define intelligence by providing an overview of different intelligence definitions and conclude that "Intelligence measures an agent's ability to achieve goals in a wide range of environments" (Legg & Hutter, 2007, p. 403). Based on this definition, a non-biological intelligence can be described as machine intelligence or AI. Spector (2006, p. 1253) describes "that intelligent behavior might best be achieved by agents that learn—agents that grow or redesign themselves to some limited extent as they confront their environments." Based on these characteristics, AI can be described as learning systems that originate from the field of computer science and independently process data, learn to recognize patterns in the data, and independently solve specific tasks (Coble et al., 2018; Fischer & Petersen, 2018; German Research Centre for Artificial Intelligence (DFKI) & Bitkom, 2017; Russell & Norvig, 2016). Due to AI's four core abilities—perception, understanding, action, and learning—and due to methods, such as machine learning and deep learning (DFKI & Bitkom, 2017), it can be concluded that AI technologies are able to identify the algorithms most efficiently (Legg & Hutter, 2007). For agriculture, this implies that AI transforms the data-driven management strategy of precision agriculture into autonomous processes that learn from the past (Jha et al., 2019), redesign themselves (Spector, 2006), and perceive their environment (e.g. farmland) while achieving the same goals, e.g., as autonomous robots (Lowenberg-DeBoer et al., 2020). From these observations and in line with Chlingaryan et al. (2018), a development towards an AI-based precision agriculture can be observed. Finger et al. (2019) describe machine learning and deep learning, which

are both methods of AI, as advanced precision farming decision support systems in terms of timing and targeting. In AI-based weed control, for instance, systems are trained based on data and images of targets (e.g., weeds) and non-targets (e.g., crops). The systems learn to distinguish between weeds and crops and how to control and remove the weeds efficiently and autonomously (Aubert et al., 2012; Partel et al., 2019).

To date, it can be observed that the development of agricultural AI systems in Germany and the political support for the development of such systems are of rather minor importance. A limited number of AI systems for agriculture are being developed by universities, industrial companies, start-ups, and other institutions such as the DFKI. However, besides these developments, studies show that AI systems for agriculture are primarily developed in the USA, Canada, Australia, and France (e.g., Jha et al., 2019; Kakani et al., 2020). In German politics, AI is generally highlighted as one of the greatest technological drivers of digitalization (German federal parliament, 2018), and the government has granted funding to the extent of three billion euros until 2025 for scientific and industrial research on AI (Federal Ministry of Education & Research, 2018). Nevertheless, at second glance, the funding is only high in a European comparison. In an international comparison, Germany lags behind countries such as the USA, China, or Israel (Groth & Straube, 2019). In addition, the German AI strategy neither specifies detailed goals nor possibilities for the implementation of AI in agriculture. The German Government (2018) only mentions that AI technologies can contribute to sustainability, resource efficiency, food security, and transparency. However, it is not only the development of AI systems and the financial support from politics that is crucial for the adoption of AI systems, but also farmers' attitude towards AI systems. It is obvious that the expected economic and ecological benefits of AI systems in agriculture can therefore only be realized if farmers are willing to adopt AI systems. Despite the financial, production, and labor-saving advantages of new technologies, the literature (see Kutter et al., 2011; Paustian & Theuvsen, 2017; Pierpaoli et al., 2013; Reichardt et al., 2009) shows that the adoption of precision agriculture technologies (PATs) is slow and that there are short term acceptance problems (Blasch et al., 2020). Although some in-field diagnostic PATs (e.g., global positioning systems and guidance systems) are already being used, more complex applications such as sensor-driven variable input applications and variable rate technologies are still not widespread (Finger et al., 2019). Thus, the expected economic and ecological potential of smart PATs are still far from being reached.

This shows that there is a discrepancy between the optimistic statements of politics, agricultural associations, market research, and industry companies about the progressive and innovative German agriculture on one hand, and the results of previous scientific studies on the adoption of PATs on the other hand. Although the mentioned advantages in the agricultural sector call for detailed examinations regarding the acceptance towards this technology, scientific research in this area is lacking. To date, there is a wide range of studies on the adoption of PATs (e.g., Barnes et al., 2019; Groher et al., 2020; Long et al., 2016; Pathak et al., 2019; Reichardt & Jürgens, 2009). However, the literature review shows that there are no empirical studies investigating the acceptance of AI systems in European or German agriculture with a behavioral perspective. Therefore, it is not known which factors influence the acceptance of AI systems in these countries.

This paper addresses this knowledge gap by investigating the acceptance of AI systems in German agriculture based on a behavioral research approach. In contrast to studies on PATs, which examine the influence of various factors on adoption, this study focusses on the preliminary stage of adoption research, i.e. acceptance research, using predictive models (Pierpaoli et al., 2013). The rationale for this decision is that in agriculture, AI is still

in an early stage of development and for various systems only prototypes exist. The aim of this study is to understand which motives and attitudes have the potential to generate a behavior shift towards a wider acceptance of AI systems. Knowing these motives is crucial to be able to convince the agricultural actors accordingly, and to design adequate strategies to promote newly launched technologies (Weersink & Fulton, 2020). Previous research on the adoption of PATs has primarily focused on farm characteristics such as farm size and location, and farmers characteristics, namely age, income, level of education, and workload (e.g., Barnes et al., 2019; Groher et al., 2020; Paustian & Theuvsen, 2017; Reichardt et al., 2009; Vecchio et al., 2020) rather than on attitudes or behavioral factors. However, some studies show that, in addition to economic cost barriers, behavioral factors such as personal interests also influence the adoption of PATs (e.g., Barnes et al., 2019; Toma et al., 2018). Thus, a deeper understanding of behavioral factors such as attitudes and motives that may stimulate a behavioral change among farmers is required. In addition, most existing studies do not examine multiple components and the complexity of adoption processes (Pathak et al., 2019). Therefore, in this study, both the TAM by Davis (1989) as well as the TPB by Ajzen (1991) are used as a theoretical framework to gain a better understanding of factors influencing farmers' behavioral intentions regarding the acceptance of AI. Due to the special characteristics of both AI and farmers, the composite model of technology acceptance and planned behavior is extended by the two factors expectation of property rights over business data and personal innovativeness. The resulting model-theoretical considerations of acceptance research are tested with a structural equation model (SEM).

This paper contributes to the literature on acceptance and adoption research regarding a new data-intensive technology in agriculture. The identification and analysis of drivers and barriers, that encourage or inhibit a change in farmers' behavior, is of great relevance to help explain the before mentioned discrepancy between the optimistic (public) perception of new technologies and rather low adoption rates for some PATs. More importantly, a deeper understanding of the connection between behavioral factors and acceptance towards AI systems could help to support the adoption of these systems in agriculture and, in this way, allow farmers to benefit from the resulting economic and ecological advantages. This paper provides insights about farmers' acceptance behavior which is important for the future development of agricultural AI systems. Policymakers, the agricultural machinery industry, and other stakeholders can use the results to realize the opportunities of AI in German agriculture.

The paper is structured as follows. In the second section, a theoretical framework on acceptance research in agriculture is presented. The TAM and the TPB are addressed and the derivation of the hypotheses is outlined. The third section describes the method, the data collection procedure, and presents the results of the empirical analysis. In the fourth section, the results are discussed and a conclusion is given.

## Theoretical framework of the composite model and hypothesis derivation

A substantial body of research on technology acceptance or adoption in agriculture focuses on PATs. These studies often refer to the US and investigate, in particular, which farm specific factors influence the adoption of certain PATs (Barnes et al., 2019; Blasch et al., 2020; Pathak et al., 2019). Some studies also investigate the adoption of PATs in Europe, albeit with differences in sampling and analysis methods. For example, Barnes et al. (2019)

examine the uptake of machine guidance and variable rate nitrogen technologies in five European countries (Belgium, Germany, Greece, the Netherlands, and the UK) using a regression model. Results show that farm size, farmers' expectations about the returns of the technology, and farmers' information-seeking behavior affect the uptake. Long et al. (2016) use qualitative interviews to explore the adoption of climate-smart agriculture innovations in four European countries (the Netherlands, France, Switzerland, and Italy). The authors identify socio-economic barriers of technology adoption, such as low awareness of climate-smart technologies, high costs, and long return of investment periods as well as regulatory and policy issues. Groher et al. (2020) investigate the adoption of driver assistance systems and activities with electronic measuring with a representative survey among farmers in Switzerland. Results of the regression analysis indicate that farm location, farm size, and the production of high-value products positively influence adoption. Vecchio et al. (2020) conduct a survey with 174 Italian farmers and find that younger and higher educated farmers as well as larger farm sizes and higher labor intensity result in higher levels of adoption. Results from a survey and choice experiment with 250 Italian farmers show that farm size, age, innovativeness, and farmers' tendency to protect the environment increase the likelihood of adoption, while high investment costs are identified as main barrier for adoption (Blasch et al., 2020). Using a mixed-methods approach with 32 Irish farmers, Das et al. (2019) identify financial resources and socio-demographics, such as age, gender, and education as influencing factors on the adoption of smart farming technologies. Toma et al. (2018) use a SEM to analyze influencing factors on the uptake of innovative crop technologies among Scottish crop farmers. Results show that economic factors, such as profit orientation, income, and farm labor as well as education, access to technological information, and perceived usefulness have an effect on technology acceptance and adoption.

For Germany, different scientific studies (e.g., Kutter et al., 2011; Paustian & Theuvsen, 2017; Reichardt & Jürgens, 2009; Reichardt et al., 2009) identify drivers and barriers to acceptance, and find that between 9 and 30% of respondents use PATs. Paustian and Theuvsen (2017) use logistic regressions to investigate the effect of farm characteristics (e.g., farm size, crops, soil quality) and farmer demographics (e.g., gender, education, farm location) on the adoption of PATs with 227 German crop farmers. In this study, a farm size of more than 500 ha arable land, experience in crop farming from 16 to 20 years or less than five years and an additional employment as agricultural contractor are identified as predictors of PATs adoption. Kutter et al. (2011) conduct qualitative interviews with 49 stakeholders from the agricultural sector and focus on communication and co-operation strategies for precision farming adoption. Agricultural contractors are mentioned as main drivers of PATs adoption, while concerns regarding data misuse, over-regulation, and software compatibility present barriers. Reichardt et al. (2009) and Reichardt and Jürgens (2009) study the adoption of precision farming with personal interviews conducted at agricultural exhibitions as well as by mail, telephone, and personal interviews. The authors conclude that the adoption of PATs in Germany is moderate and identify high costs, a complicated use of the technology, and a small field size as main barriers to adoption. Further studies on technology adoption among farmers are conducted by Michels et al. (2020a, b, c). A representative study on the adoption and use of smartphones among German farmers ( $n=817$ ) shows that smartphone ownership decreases with increasing age and smaller farms, whereas smartphone ownership is more likely with higher education, computer literacy, and farmers' self-reported innovativeness (Michels et al., 2020b). Furthermore, based on the unified theory of acceptance and use of technology-framework by Venkatesh et al. (2003), a SEM is used to investigate the adoption of smartphone apps in crop production among 207 farmers (Michels et al., 2020a). The adoption of drones by German

farmers ( $n = 167$ ) is influenced by farmers' age, precision agriculture literacy, and farm size (Michels et al., 2020c). Overall, it is difficult to accurately estimate and compare the adoption rates of PATs as well as the barriers and drivers of technology adoption in these studies since different definitions of PATs, different influencing factors as well as different sampling and analysis methods are used. Moreover, behavioral based approaches to identify adoptions drivers and barriers are (generally) rare.

In the literature on acceptance and adoption research, several models explaining the adoption of new technologies are discussed. Rogers' (2003) theory of diffusion of innovations (DOI) and Davis' (1989) TAM are identified as the key theoretical models of adoption research. The DOI theory focuses on characteristics of a technology, whereas the TAM aims at predicting behavioral attitudes towards a technology and is according to Venkatesh (2000) a widely applied model for acceptance research. Due to its predictive design, the TAM includes the factor acceptance as a behavioral intention and therefore as a preliminary stage of adoption (Bagozzi & Lee, 1999; Pierpaoli et al., 2013). Since AI systems for agriculture are still in an early stage of development, this analysis focuses on acceptance instead of adoption and thus relies to the TAM. In order to increase the complex understanding of AI acceptance, the TAM is extended by the TPB which is a widely used theory for predicting and explaining behavior in various research areas (Sok et al., 2020). This approach of model composition is supported by Pathak et al. (2019) who mention that the TPB has the potential to capture further attitudes and beliefs about technology acceptance and by Davis (1993) who recommends an extension of the TAM by behavioral factors. Model compositions are applied in various studies, e.g., on the acceptance of genetically modified seeds (Voss et al., 2009), sustainable cultivation methods (Dessart et al., 2019), transport packaging (Kamrath et al., 2018), or operational specialization and diversification decisions (Hansson et al., 2012). Since a context-specific extension of TPB models is required to adequately predict behavior or behavioral intentions (see Sniehotta et al., 2014), the composite model is extended by the two context specific factors expectation of property rights over business data and personal innovativeness. Therefore, in total, the following factors are examined:

- (1) Perceived usefulness
- (2) Perceived ease of use
- (3) Personal attitude
- (4) Perceived social norm
- (5) Perceived behavioral control
- (6) Expectation of property rights over business data
- (7) Personal innovativeness

### Technology acceptance model

The acceptance of innovations represents a decision-making process that is characterized by determinants of acceptance and resistance and is a crucial construct for explaining (un) successful innovations (Königstorfer, 2008). In order to investigate the acceptance of technological innovations, Davis (1989) developed the TAM. The TAM consists of the two factors, perceived usefulness and perceived ease of use, which have proven to be important predictors for the acceptance of new technologies (Aubert et al., 2012; Venkatesh, 2000). Both factors can explain up to 40% of the total variance in behavioral intention (Venkatesh & Davis, 2000) and have already been investigated in studies on precision farming (e.g.,

Aubert et al., 2012; Reichardt et al., 2009; Rezaei-Moghaddam & Salehi, 2010). In the following, the hypotheses for the corresponding factors are derived.

Factor 1 “*perceived usefulness*”: This factor measures the extent to which potential users assume that the use of the technology contributes to an easier performance of work tasks (Davis, 1989; Von Alvensleben & Steffens, 1990). According to Venkatesh et al. (2003), who describe this factor as performance expectancy, a positive effect on acceptance is postulated. Thus, a favorable use is assumed to positively influence and increase the acceptance of new technologies, i.e. in this study AI systems (e.g., Aubert et al., 2012; Davis, 1989; Michels et al., 2020a; Rezaei-Moghaddam & Salehi, 2010; Venkatesh, 2000). Hence, the first hypothesis is:

**H1** A more positive perceived usefulness of AI systems in agriculture positively influences the acceptance of AI systems in agriculture.

Factor 2 “*perceived ease of use*”: This factor includes the assessment of the application by potential users, and refers to the user-friendliness of a system which is described by Venkatesh et al. (2003) as effort expectancy. An easy use of applications is expected to positively influence the *acceptance of AI systems* (e.g., Aubert et al., 2012; Davis, 1989; Michels et al., 2020a; Venkatesh, 2000). Hence, the second hypothesis is:

**H2** A more positive perceived ease of use of AI systems in agriculture positively influences the acceptance of AI systems in agriculture.

Davis (1989), in particular, as well as further authors (e.g., Rezaei-Moghaddam & Salehi, 2010; Venkatesh, 2000) determine that the *perceived ease of use* has a positive influence on the *perceived usefulness*. Hence, the following hypothesis is derived:

**H2a** A more positive perceived ease of use of AI systems in agriculture positively influences the perceived usefulness of AI systems in agriculture.

## Theory of planned behavior

Building on the theory of reasoned action (Fishbein & Ajzen, 1975), the TPB (Ajzen, 1991) represents an explanatory and predictive model of attitudinal-behavioral reactions based on the three factors, attitude, subjective norm, and perceived behavioral control. The TPB is widely applied to explain and predict behavior (including farmer behavior) and provides an empirically based framework (Sok et al., 2020). Furthermore, Sok et al. (2020) state that when using the TPB in research, it is important to define behavior in terms of the target object, the action performed, the context, and the time period. The general idea of the TPB is that the more positive the factors are evaluated, the stronger the behavioral intention, i.e., the acceptance. The relative explanatory share of the factors on the behavioral intention differs depending on the situation (Ajzen, 1991).

Factor 3 “*personal attitude*”: This factor captures the degree to which the behavior in question is assessed positively or negatively (Ajzen, 1991). In this study, *personal attitude* towards a specific behavior is measured as the attitude towards the intention of using AI systems in agriculture. Hence, the third hypothesis is:

**H3** A more positive personal attitude towards AI systems in agriculture positively influences the acceptance of AI systems in agriculture.

Factor 4 “*perceived social norm*”: In the TPB, this factor is described as subjective norm and refers to the perceived social pressure by stakeholders or others to perform or not perform the related behavior (Ajzen, 1991; Sok et al., 2020). Since the objective of this factor is to behave according to normative pressure, this factor is defined as the *perceived social norm* in this study. To put this in perspective, society’s expectations towards agriculture are explained with a focus on Germany. To date, public knowledge of agricultural production processes is rather limited. Due to the alienation of society from food production, the media increasingly shape ideas about agricultural production processes (Pfeiffer et al., 2021). On the one hand, an idyllic image of agricultural production is conveyed through media representations (Albersmeier et al., 2008). On the other hand, automation and specialization in agriculture are criticized. Von Alvensleben and Steffens (1990) already observed early on that criticism of innovative agricultural production methods had been emerging among the population which has remained present until today. There is a general concern about alienation from a naturally to a technically oriented food production. At the same time, consumers are demanding environmentally friendly farming practices and greater animal welfare (Zander et al., 2013), which could be achieved by using new technologies. According to this, a conflict of interest is emerging between societal expectations of natural and sustainable agriculture, and technical developments in the agricultural sector which could reduce public acceptance of a more digitalized agriculture (Dessart et al., 2019; Pfeiffer et al., 2021). Thus, this factor relates to the farmers’ perception of what the public or stakeholders expect in terms of their willingness to use a new technology such as AI systems. Acknowledgement of technical agriculture in society and politics drives the use of AI systems in agriculture (Ajzen, 1991; Dessart et al., 2019; Michels et al., 2020a). Hence, the fourth hypothesis is:

**H4** A more positive perception of social norms positively influences the acceptance of AI systems in agriculture.

Factor 5 “*perceived behavioral control*”: This factor captures the perceived simplicity or difficulty in implementing a behavior (Ajzen, 1991). It therefore represents the respondent’s self-confidence in his or her own abilities to use AI systems. Hence, the fifth hypothesis is:

**H5** A more positive perceived behavioral control positively influences the acceptance of AI systems in agriculture.

### Contextual model extension

In addition to the above-mentioned factors influencing the acceptance of AI systems in agriculture, further factors could affect AI acceptance, namely, farmers’ expectation of property rights over business data and farmers’ personal innovativeness.

Factor 6 “*expectation of property rights over business data*”: Questions of data management and data sovereignty will play a crucial role in a digitalized agriculture and are regarded as critical issues for the future development of new technologies in agriculture (Bovensiepen et al., 2016; Finger et al., 2019; Walter et al., 2017). Kutter et al. (2011) note



that farmers fear data misuse. In a media analysis, Gandorfer et al. (2017) find that data sovereignty is a barrier to acceptance. It is expected that the use of intelligent technologies will be affected by unresolved issues concerning the ownership of data, the protection of privacy, and information technology security or data misuse (Vogel, 2020; Wolfert et al., 2017). Agricultural data are important for farmers and other actors in the value chain to reduce risks, e.g., regarding yield projections, diseases, and weather forecasts (Dalhaus & Finger, 2016; Walter et al., 2017). Simultaneously, access to reliable agricultural data is essential for the development of digitalization in agriculture (European Crop Protection Association (ECPA), 2018). On the one hand, data serve as input for production and decision-making processes. On the other hand, however, data represent the output of various work processes which farmers consider as sensitive information (Antle, 2019). The German Agricultural Association, politicians, and the industry demand that the data sovereignty should be in the hands of farmers (German Agricultural Association, 2018; Schrijver et al., 2016). Data ownership rights could create markets for data production and use (Antle, 2019). In contrast, legal experts argue that there should be no right of data ownership under German civil law (Martinez, 2018; Zimmer, 2018) since much of the data collected are not considered to be private goods as their use is neither rival nor exclusive (Antle, 2019). Legal experts argue that property rights only exist for physical objects where competing uses are not possible. Since data are machine readable information, they do not cause any conflicting situation as they can be used and reproduced by several people. If there were property rights over data, individuals would be excluded from using them which would reduce social welfare (Zimmer, 2018). One approach to clarify unresolved questions regarding data sovereignty is the European code of conduct on agricultural data sharing adopted in April 2018. The voluntary code of conduct sets out contractual arrangements for the sharing of agricultural data and indicates that the control of access to, and the use of farm data should lie with the data collector, in this case, the farmer. The aim of the code of conduct is to create trust, clarify responsibilities, and to establish transparent principles (ECPA, 2018). However, confidentiality requirements concerning farm and personal data for farmers are needed (Finger et al., 2019). It can be assumed that if the ownership of business data lies with the farmer, then the willingness to use AI systems will increase. Hence, the sixth hypothesis is formulated:

**H6** A farmer's expectation of property rights over business data positively influences the acceptance of AI systems in agriculture.

Factor 7 “*personal innovativeness*”: This factor describes a person's interest or willingness to try out a new technology (Rogers, 2003) and is widely included in studies on behavioral intention and usage behavior of new technologies (e.g., Aubert et al., 2012; Barnes et al., 2019; Michels et al., 2020b; Zampou et al., 2012). In line with Aubert et al. (2012) and Michels et al. (2020b) who determine a positive, statistically significant influence of farmers' innovativeness on the acceptance of PATs or smartphone ownership, the following hypothesis is:

**H7** A farmer's innovativeness positively influences the acceptance of AI systems in agriculture.

It is postulated that *personal innovativeness* also influences factors relating to the farmer himself or the farm on which the respondent works. Therefore, the following hypotheses

on *perceived usefulness, perceived ease of use, personal attitude, and perceived behavioral control* are derived:

**H7a** A farmer's innovativeness positively influences the perceived usefulness of AI systems in agriculture.

**H7b** A farmer's innovativeness positively influences the perceived ease of use of AI systems in agriculture.

**H7c** A farmer's innovativeness positively influences the personal attitude towards of AI systems in agriculture.

**H7d** A farmer's innovativeness positively influences the perceived behavioral control of AI systems in agriculture.

Several studies investigating farmers' acceptance behavior toward PATs in Germany extend their research model by farm or machine-specific factors, such as expected costs, machine compatibility, farm size, educational level, and age (e.g., Kutter et al., 2011; Paus-tian & Theuvsen, 2017; Reichardt et al., 2009). However, since the analysis in this study focuses on behavioral aspects, these factors are not examined.

## Empirical analysis

### Method and construct operationalization

SEM are suitable for the analysis of complex cause-effect structures and are used in acceptance and adoption research on PATs as well as on TPB research (e.g., Aubert et al., 2012; Michels et al., 2020a; Rezaei-Moghaddam & Salehi, 2010; Sok et al., 2020; Toma et al., 2018). The method allows measurement of hypothetical constructs, i.e. latent variables that are not directly measurable, such as attitudes and behavioral intentions. A SEM consists of a structural model and a measurement model. The structural model represents the assumed relationships between the constructs. The measurement model shows the relationship between the constructs and their indicators. A distinction is made between reflective and formative measurement models, both of which are used in this study. A reflective measurement model means that the hypothetical construct causes the indicators. The indicators, which are also referred to as statements, should be interchangeable by other indicators, the indicators' topic should be similar, and covariances between the indicators of a construct are necessary. In formative measurement models, the indicators cause the construct. Changes of indicators lead to changes in the constructs (Jarvis et al., 2003). The measurability of the hypothetical constructs is achieved through operationalizing the factors by using several indicators that represent

different aspects of the constructs (Hair et al., 2016; Sok et al., 2020). Thus, measuring hypothetical constructs by multiple statements is denoted as operationalization. The conceptualization of the hypothetical constructs is an important step to explain behavior and should be based on established guidelines such as the use of existing literature (Sok et al., 2020). In this study, whenever possible, it was adhered to existing literature. Respondents' agreement with the different statements was measured using a six-level verbal-numerical scale ranging from "(1) strongly disagree" to "(6) strongly agree". For the indicators marked with (R) (see Tables 1, 2, 3, 6), reversed (negated) statements were used to prevent respondents from always marking the response options on the right of the survey when agreeing. For these statements, a low value on the verbal-numerical scale means that the AI system will be supported. The coding of these indicators was reversed since for the results evaluation all indicators should be in the same direction in order to test the hypotheses. The entire questionnaire was pre-tested with both agricultural researchers and farmers to ensure comprehensibility of each item. To avoid sequence effects, the indicators within the different constructs were displayed randomly in the questionnaire. The operationalization of the factors, which was based on existing studies on acceptance research, is explained below. In total, the questionnaire included 39 indicators. However, at this point, only those indicators (29) are presented which fulfilled the quality criteria in the (following) structural equation analysis (see Appendix Tables 12 and 13). Since the data collection was based on two samples (see next section), differences in the response behavior are indicated by the mean values for each item. Mann–Whitney U tests were used to check for statistically significant differences in response behavior between the two groups.

The reflectively measured construct *acceptance of AI systems* was measured by two factors (see Table 1). The indicators were derived from the study by Zarpou et al. (2012) on the use of mobile services. These and the indicators of the following constructs were translated into German and adapted to the context of this study. The temporal reference in item [A1] corresponds to the AI strategy of the German government.

**Table 1** Operationalization *acceptance of AI systems*

Indicator name	Indicator description	Mean per group		p value
		1 (n=36)	2 (n=47)	
	To what extent do you agree with the following statements? "I think that ...			
[A1]	... my interest in self-learning machines will increase until 2025."	4.56	3.89	0.008***
[A2] (R)	... I will never use self-learning machines."	2.36	2.36	0.943

(R) denotes reverse coded data. Farmers in group 1 were contacted through the university and received an online survey. Farmers in group 2 were located in southern Hesse and received a paper survey. Mann–Whitney U tests were used to test for significant differences between group 1 and group 2

\* $p \leq 0.1$ , \*\* $p \leq 0.05$ , \*\*\* $p \leq 0.01$

The reflectively measured construct *perceived usefulness* was measured based on four statements concerning workload, suitability, and productivity which were derived from the contributions of Davis (1989) and Oh et al. (2003) (see Table 2).

**Table 2** Operationalization *perceived usefulness*

Indicator name	Indicator description	Mean per group		p value
		1 (n = 36)	2 (n = 48)	
	To what extent do you agree with the following statements? “I think that the use of self-learning machines...			
[PU1]	... enables me to complete work tasks on my farm faster than before.”	3.83	3.52	0.252
[PU2]	... increases the productivity of my farm.”	4.31	3.58	0.004***
[PU3]	... makes work easier for all the workers on my farm.”	4.08	3.81	0.351
[PU4] (R)	... is unsuitable for my agricultural business.”	2.22	3.27	0.001***

(R) denotes reverse coded data. Farmers in group 1 were contacted through the university and received an online survey. Farmers in group 2 were located in southern Hesse and received a paper survey. Mann–Whitney U tests were used to test for significant differences between group 1 and group 2

\* $p \leq 0.1$ , \*\* $p \leq 0.05$ , \*\*\* $p \leq 0.01$

The formatively measured construct of *perceived ease of use* was captured by five statements. The indicators of the construct were based on the contributions of Davis (1989) and Oh et al. (2003) (see Table 3).

**Table 3** Operationalization *perceived ease of use*

Indicator name	Indicator description	Mean per group		p value
		1 (n = 36)	2 (n = 47)	
	To what extent do you agree with the following statements? “For me ...			
[PEOU1]	... the operation of self-learning machines is easy to learn.”	4.53	3.77	0.001***
[PEOU2]	... working with self-learning machines is possible without any problems.”	3.97	3.55	0.105
[PEOU3] (R)	... the application possibilities of self-learning machines are not comprehensible.”	2.78	2.52 <sup>a</sup>	0.513
[PEOU4]	... the use of self-learning machines allows for more flexibility in the operating process.”	4.14	3.83	0.179
[PEOU5] (R)	... it is difficult to skillfully operate self-learning machines.”	2.69	3.13	0.072

(R) denotes reverse coded data.

<sup>a</sup>(n = 46). Farmers in group 1 were contacted through the university and received an online survey. Farmers in group 2 were located in southern Hesse and received a paper survey. Mann–Whitney U tests were used to test for significant differences between group 1 and group 2

\* $p \leq 0.1$ , \*\* $p \leq 0.05$ , \*\*\* $p \leq 0.01$

The formatively measured construct *personal attitude* was measured by four statements on the assessment and evaluation of AI systems derived from the contributions of Kamrath et al. (2018) and Hansson et al. (2012) (see Table 4).

**Table 4** Operationalization *personal attitude*

Indicator name	Indicator description	Mean per group		p value
		1 (n=36)	2 (n=47)	
	To what extent do you agree with the following statements? "I think that ...			
[PA1]	... self-learning machines can reduce pesticide use on my farm."	4.17	4.62	0.377
[PA2]	... it is important to make German agriculture more sustainable through the use of self-learning machines."	4.28	4.04	0.235
[PA3]	"I am interested in exploring new technological developments for agriculture."	4.33	4.20 <sup>a</sup>	0.295
[PA4]	"I could imagine to include self-learning machines to my current agricultural machinery."	3.28	3.55	0.403

<sup>a</sup>(n=46). Farmers in group 1 were contacted through the university and received an online survey. Farmers in group 2 were located in southern Hesse and received a paper survey. Mann–Whitney U tests were used to test for significant differences between group 1 and group 2

\*p ≤ 0.1, \*\*p ≤ 0.05, \*\*\*p ≤ 0.01

The formatively measured construct *perceived social norm* referred to the perceived social pressure and political support (see Table 5). Indicators which were related to social pressure from other stakeholders such as non-governmental organizations and media did not fulfill the quality criteria of validity and reliability of SEM and are therefore not displayed.

**Table 5** Operationalization *perceived social norm*

Indicator name	Indicator description	Mean per group		p value
		1 (n=36)	2 (n=48)	
	To what extent do you agree with the following statements?			
[PSN1]	"Policymakers strongly support modern agriculture."	2.36	2.17	0.346
[PSN2]	"The use of self-learning systems on farms is in line with society's expectations of agriculture."	2.97	3.34 <sup>a</sup>	0.096*

<sup>a</sup>(n=47). Farmers in group 1 were contacted through the university and received an online survey. Farmers in group 2 were located in southern Hesse and received a paper survey. Mann–Whitney U tests were used to test for significant differences between group 1 and group 2

\*p ≤ 0.1, \*\*p ≤ 0.05, \*\*\*p ≤ 0.01

Three statements (see Table 6) measured the construct of *perceived behavioral control* formatively. To capture the self-efficacy belief, i.e., according to Ajzen (1991, p. 188) "the perceived ease or difficulty of performing the behavior", it was referred to the interviewees' assessments of expected experiences and difficulties in using AI systems.

**Table 6** Operationalization *perceived behavioral control*

Indicator name	Indicator description	Mean per group		p value
		1 (n=36)	2 (n=47)	
	To what extent do you agree with the following statements?			
[PBC1] (R)	“For me it will be difficult to use self-learning machines instead of the current machines.”	3.47	3.61 <sup>a</sup>	0.431
[PBC2]	“I am the person who decides on the use of self-learning machines on the farm I work on.”	2.83	4.00	0.003***
[PBC3]	“I think it is very important to use self-learning machines on farms.”	3.92	3.70	0.197

(R) denotes reverse coded data

Farmers in group 1 were contacted through the university and received an online survey. Farmers in group 2 were located in southern Hesse and received a paper survey. Mann–Whitney U tests were used to test for significant differences between group 1 and group 2

<sup>a</sup>(n=46)

\* $p \leq 0.1$ , \*\* $p \leq 0.05$ , \*\*\* $p \leq 0.01$

Both the industry and the German Agricultural Association as well as politicians demand that business data property rights should lie with the farmers (German Agricultural Association, 2018). The indicators of the formatively measured construct *expectation of property rights over business data* which were used in this study are presented in Table 7.

**Table 7** Operationalization *expectation of property rights over business data*

Indicator name	Indicator description	Mean per group		p value
		1 (n=36)	2 (n=47)	
	To what extent do you agree with the following statements?			
[PR1]	“The operating data belong to the farmers.”	4.78	4.72	0.803
[PR2]	“Stricter regulations on data protection reduce the competitiveness of German agriculture.”	3.08	3.47	0.328
[PR3]	“A code of conduct can regulate the basic principles for the use of operating data.”	4.00	3.96 <sup>a</sup>	0.684
[PR4]	“A government raw data platform must be established for the exchange of operating data.”	5.26	2.69 <sup>b</sup>	0.582
[PR5]	“The control of the data flow is up to the farmers.”	3.33	3.04 <sup>c</sup>	0.363

(R) denotes reverse coded data

Farmers in group 1 were contacted through the university and received an online survey. Farmers in group 2 were located in southern Hesse and received a paper survey. Mann–Whitney U tests were used to test for significant differences between group 1 and group 2

<sup>a</sup>(n=45)

<sup>b</sup>(n=42)

<sup>c</sup>(n=48)

\* $p \leq 0.1$ , \*\* $p \leq 0.05$ , \*\*\* $p \leq 0.01$

The reflectively measured construct *personal innovativeness* describes the interest of a person to explore a new technology and was based on the statements from the contributions of Aubert et al. (2012) and Zampou et al. (2012) (see Table 8).

**Table 8** Operationalization *personal innovativeness*

Indicator name	Indicator description	Mean per group		p value
		1 (n=36)	2 (n=48)	
	To what extent do the following statements about applications with new technologies* in general apply to you? *(Speakers with speech recognition, drones, GPS devices and more)			
[PI1]	“I am very curious about how applications with new technologies work.”	4.57	4.33	0.118
[PI2]	“I like to explore applications with new technologies.”	4.31	4.23	0.609
[PI3]	“I enjoy being around people who are exploring new technologies.”	4.39	4.23	0.091*
[PI4]	“I often seek information on new technologies.”	4.47	3.98	0.029**

Farmers in group 1 were contacted through the university and received an online survey. Farmers in group 2 were located in southern Hesse and received a paper survey. Mann–Whitney U tests were used to test for significant differences between group 1 and group 2

\* $p \leq 0.1$ , \*\* $p \leq 0.05$ , \*\*\* $p \leq 0.01$

## Data collection

Contacting farmers and collecting their data for scientific research is generally a challenge and thus also in this study. In the scientific literature on acceptance research in German agriculture, various sampling approaches are applied (see section 2). Researchers use, for example, surveys at agricultural exhibitions (e.g., Reichardt & Jürgens, 2009), qualitative face-to-face or phone interviews (e.g., Kutter et al., 2011), and postings in social networks (e.g., Michels, et al., 2020a; Paustian & Theuvsen, 2017). However, unbiased data collection from farmers is nearly impossible except from cost-intensive surveys via commercial survey companies that allow for representative surveys. In this study, two approaches were used, that is, data was collected both online and offline. Differences in response behavior between the two groups were reported for each item in Tables 1, 2, 3, 4, 5, 6, 7, 8 (see previous section). The first approach was an online survey that was sent to agricultural students and employees of a university in Hesse (Germany) via the IT Service Centre in October 2019. The participants were only interviewed if they work on an agricultural farm that includes crop production. The second approach to recruit farmers as study participants was carried out on the basis of a cooperation project between the university and a water supplier in southern Hesse. Since the project involves field studies on the economic and nitrogen efficiency of precision farming, all farmers produce crops. The farmers in southern Hesse were surveyed via a paper survey between November 2019 and March 2020. The surveys were handed out by a project member with a stamped return envelope and a time limit for participation of two months. Duplicate participation was ruled out based on the provision of the participants' e-mail address. As an incentive to participate, a draw of five vouchers for a

German retailer that sells workwear and protective equipment was offered. The authors of this study deliberately decided against interviewing farmers via social networks in order to avoid a self-selection bias since it can be assumed that farmers who use social networks have a higher affinity for digitalization than the average farmer. Furthermore, it is hard to verify whether the accounts in social networks are used by real people.

The survey started with an introduction providing information on the topic of the survey, the expected time for answering the questions, and the lottery. Then, the participants were asked to respond to the statements which represented the eight constructs of the composite model. In order to create a common understanding of AI systems in agriculture among the farmers surveyed, the questionnaire included the following explanation which was presented after the statements on *personal innovativeness*, the majority of the statements on the *perceived social norm*, and the statements on *expectation of property rights over business data*, and before the statements of the TAM and TPB constructs (see online supplementary material).

“Self-learning systems or machines are computer science applications that process data independently, learn to recognize patterns from data, and solve specific tasks. This so-called intelligent behavior is integrated in machines, for example robots or computers. In agriculture, self-learning systems can perceive their environment and autonomously search for solutions. These machines usually drive autonomously across the field and can distinguish weeds from crops and thereby remove the former one.”

This was followed by one open-ended question on the main barriers for AI acceptance as well as some questions on socio-demographics and farm characteristics. At the end, the farmers were required to enter their e-mail address.

In this survey, the term AI systems was described by the term self-learning systems (in German: “selbstlernende Systeme”) to avoid negative and dystopian associations with the term AI. A synonymous use of the two terms is also applied in the opinion piece by DFKI and Bitkom (2017) and in publications of the Federal Ministry for Economic Affairs and Energy (2019). The AI definition in the survey was developed by referring to the AI design explained in the introduction of this study. Since all survey participants were involved in crop production, a short example of a prototype of an intelligent agent was provided which resembled the description of a field crop robot by Lowenberg-DeBoer et al. (2020). In addition, this AI survey definition fulfilled the above-mentioned requirements on TPB research discussed by Sok et al. (2020). It described the target object (here: self-learning system), the action performed (here: processing, learning, recognizing, and solving tasks), and the context in which it occurs (here: AI in agriculture). The time period as fourth condition was fulfilled by specifying the year 2025 in item [A1].

To investigate the research model, the variance based Partial Least Squares (PLS) method was used. This particular approach was chosen because the SEM contained both formative and reflective measurement models and the assumption of normal distribution was not fulfilled. In PLS-SEM, hypothetical relationships of latent variables are predicted by maximizing the explained variance in the dependent variable as in an Ordinary Least Squares (OLS) regression. Accordingly, the PLS-SEM is an estimation method based on an OLS regression for the measurement of multi-item constructs. PLS-SEM is particularly suitable for forecasting purposes and for analyses with a small sample size (Hair et al., 2016).



## Results

In total, 84 persons completed the survey. 43% ( $n=36$ ) of participants originated from the survey with university members (group 1) while 57% ( $n=48$ ) of the respondents were farmers from southern Hesse (group 2). Due to outliers in the respondents' answers, the median is reported in Table 9 for the descriptive statistics. Since in Germany only 36% of the farmers are between 25 and 44 years old (Federal Statistical Office, 2017), the sample in this study is rather young with an average age of 33.5 years. Compared to Germany where 69% of all farmers are male (Federal Statistical Office, 2017), the share of male farmers (87%) in this study is above-average (Table 10). In comparison to the German (Hessian) average where 60.50 ha (47.00 ha) of land are cultivated per farm (Federal Statistical Office, 2017), the farmers in this study cultivate an above-average amount of arable land with a median of 107.00 ha. Furthermore, 85% (11%) of the respondents state that their main business area is crop production (livestock farming). Further group-specific data are presented in Tables 9 and 10. The total sample size of this study is in line with the recommendation of Chin (1998) who states that it should be at least ten times larger than the number of indicators in the most complex formative model.

The results from the PLS-SEM are evaluated in two steps. First, the outer models (reflective and formative measurement model) are evaluated followed by the inner model (structural model) in a second step. Missing values are replaced by mean values (see Tables 1, 2, 3, 4, 5, 6, 7, 8). The examination of the reflective measurement models reveals that the quality criteria of indicator reliability (loadings  $\geq 0.7$ ), convergence validity (average variance extracted (AVE)  $\geq 0.5$ ), and internal consistency ( $P_c \geq 0.6$ ) are satisfied (see Appendix Table 12). This is also the case for the formative measurement models. The variance inflation factors (VIF) are less than five suggesting that there are no critical levels of multicollinearity. In addition, the relevance and significance of the indicators are validated using a bootstrap procedure. The weights ( $\geq 0.1$ ) and loadings ( $> 0.5$ ) are satisfactory and significant (see Appendix Table 13). Accordingly, the second step of SEM estimation and thus, the testing of the hypothesized relationships follows.

Structural models represent presumed relationships between various constructs (Hair et al., 2016). The VIF results of the structural model indicate that collinearity is not a major problem. Since the Stone-Geisser criterion ( $Q^2$ ) is higher than zero, it can be concluded that the model includes constructs that influence the acceptance of AI systems in

**Table 9** Descriptive statistics for socio-demographics and farm characteristics I

Variable	Sample	Description	Min	Max	Median	
					Per group (SD)	Total (SD)
Age ( $n=82$ )	Group 1 ( $n=35$ )	Farmers' age in years	19	58	25.00 (7.76)	
	Group 2 ( $n=47$ )		19	67	50.00 (12.46)	
Employees ( $n=83$ )	Group 1 ( $n=36$ )	Number of employees (including farm manager)	1	25	4.00 (3.95)	
	Group 2 ( $n=47$ )		1	6	3.00 (1.39)	
Arable land ( $n=83$ )	Group 1 ( $n=35$ )	Arable land in hectares	4	750	120.00 (196.47)	
	Group 2 ( $n=48$ )		22	290	100.50 (53.00)	

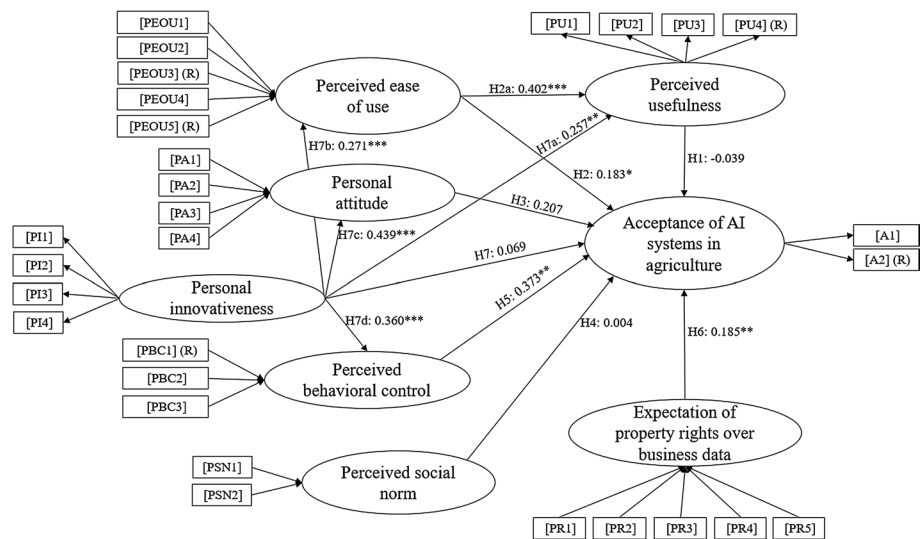
Deviations from the sample size result from incomplete responses from respondents

SD standard deviation

**Table 10** Descriptive statistics for socio-demographics and farm characteristics II

Variable	Sample	Description	Percent per group (%)	Percent total (%)
Gender (n = 82)	Group 1 (n = 35)	Male farmers	74	87
	Group 2 (n = 47)		96	
Type of business (n = 83)	Group 1 (n = 36)	Main acquisition	69	74
	Group 2 (n = 47)		77	
Crop production (n = 71)	Group 1 (n = 29)	Main business area is	81	85
	Group 2 (n = 42)	crop production	88	

Deviations from the sample size result from incomplete responses from respondents



**Fig. 1** Structural equation model for the acceptance of AI systems in agriculture. The indicators are shown in boxes and the hypothesized constructs are indicated within ellipses. The arrows between the ellipses represent the established hypotheses. Path coefficients are reported for the respective hypothesis. \* $p \leq 0.1$ , \*\* $p \leq 0.05$ , \*\*\* $p \leq 0.01$

agriculture. According to the size of  $Q^2 = 0.295$ , a medium–high forecast relevance can be assigned to the tested model (Hair et al., 2016). Furthermore, the PLS-SEM aims at maximizing the  $R^2$  and values above 0.50 are considered moderate (Hair et al., 2016). In this model, 59% of the variance of the acceptance of AI systems is explained by the factors examined. Figure 1 presents the results of the hypothesis testing carried out using Smart-PLS 3 (Ringle et al., 2015).

Table 11 shows the hypothesis testing by indicating the path coefficients, p-values, and the corresponding results. Path coefficients show the relationships between the hypothetical constructs in the SEM and can be understood as standardized beta coefficients (Hair et al., 2016). To assess the significance of the path coefficients, bootstrapping with 5,000 sub samples was applied. In general, the higher the path coefficient, the higher the relevance of the construct for the dependent variable *acceptance of AI systems*. The estimation

of the measurement model of the dependent variable indicates that acceptance is measured by the increasing interest in AI machines until 2025 as well as a prospective use without exact time reference.

Due to the small sample size of this study, hypotheses with a significance level of 10% are supported. Additionally, the levels of the path coefficients are interpreted to assess the economic relevance of the respective construct. The hypotheses tests indicate that eight out of twelve hypotheses are supported. For the factors of the TAM, a statistically significant influence of the *perceived ease of use* on the *acceptance of AI systems* is found (H2). The *perceived ease of use* also indicates a statistically significant influence on the *perceived usefulness* (H2a). The hypothesis on the influence of the *perceived usefulness* on the *acceptance of AI systems* (H1) is rejected as no significant effect is noted.

The results for the factors of the TPB show that hypothesis H5 on *perceived behavioral control* is confirmed. The *perceived social norm* (H4) as well as farmers' *personal attitude* (H3) have no statistically significant influence on the *acceptance of AI systems*. However, due to the comparatively high path coefficient and a p-value of 0.116 (see Table 11), it can be assumed that farmers' *personal attitude* towards AI systems could be an economically relevant factor for the *acceptance of AI systems*.

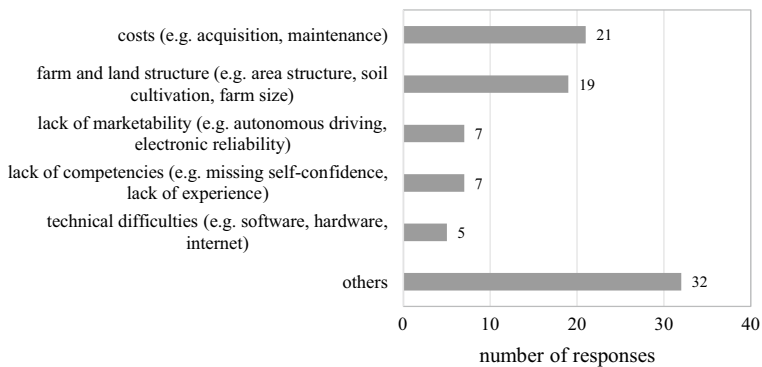
The hypothesis regarding farmers' *expectation of property rights over business data* (H6) is confirmed, whereas the path coefficient of *personal innovativeness* (H7) shows no statistically significant effect on the *acceptance of AI systems*. However, the analysis shows a statistically significant influence of *personal innovativeness* on the constructs measured by statements referring to the respondent himself or his farm (H7a–H7d). The strongest influence of *personal innovativeness* is on farmers' *personal attitude* towards AI systems in agriculture (H7c: 0.439\*\*\*), followed by the *perceived behavioral control* (H7d: 0.360\*\*\*). The total effect of *personal innovativeness* (0.329\*\*\*), that is both the direct and indirect effect (Hair et al., 2016), has a statistically significant influence on *AI acceptance* in agriculture as displayed in Table 11. Furthermore, it can be noted that the *perceived ease of use* is a comparatively stronger driver for the *perceived usefulness* of AI systems (H2a) than *personal innovativeness* (H7a). A further comparison of the path coefficients indicates that the *perceived behavioral control* has the strongest influence on the *acceptance of AI systems* (H5: 0.373\*\*). The second strongest, albeit insignificant effect is determined for farmers' *personal attitude* (H3: 0.207), followed by farmers' *expectation of property rights over business data* (H6: 0.185\*\*) and the *perceived ease of use* (H2: 0.183\*).

In addition to the quantitative evaluation, an exploratory approach was used to identify further acceptance barriers. The survey participants were invited to answer an open-ended question on the expected difficulties in the future use of AI systems at the end of the survey (before the question on the socio-demographics). Since this was not a mandatory question, only 82% of the respondents (n=69) answered it. Multiple answers were possible. Therefore, in total 91 barrier reasons were named which are assigned to different categories (see Fig. 2). The results show that costs are the most frequently mentioned acceptance barrier, followed by farm and land structures. The lack of marketability, missing competencies as well as technical difficulties are further mentioned barriers.

**Table 11** Results of the hypothesis testing

Hypothesis	Path coefficient (p-value)	Results
H1 A more positive perceived usefulness of AI systems in agriculture positively influences the acceptance of AI systems in agriculture	− 0.039 (0.379)	Not supported
H2 A more positive perceived ease of use of AI systems in agriculture positively influences the acceptance of AI systems in agriculture	0.183* (0.079)	Supported
H2a A more positive perceived ease of use of AI systems in agriculture positively influences the perceived usefulness of AI systems in agriculture	0.402*** (0.001)	Supported
H3 A more positive personal attitude towards AI systems in agriculture positively influences the acceptance of AI systems in agriculture	0.207 (0.116)	Not supported
H4 A more positive perception of social norms positively influences the acceptance of AI systems in agriculture	0.004 (0.479)	Not supported
H5 A more positive perceived behavioral control positively influences the acceptance of AI systems in agriculture	0.373** (0.013)	Supported
H6 A farmer's expectation of property rights over business data positively influences the acceptance of AI systems in agriculture	0.185** (0.032)	Supported
H7 A farmer's innovativeness positively influences the acceptance of AI systems in agriculture	0.069 (0.261)	Not supported
H7a A farmer's innovativeness positively influences the perceived usefulness of AI systems in agriculture	0.257** (0.011)	Supported
H7b A farmer's innovativeness positively influences the perceived ease of use of AI systems in agriculture	0.271 *** (0.003)	Supported
H7c A farmer's innovativeness positively influences the personal attitude towards of AI systems in agriculture	0.439*** (0.000)	Supported
H7d A farmer's innovativeness positively influences the perceived behavioral control of AI systems in agriculture	0.360*** (0.001)	Supported

\* $p \leq 0.1$ , \*\* $p \leq 0.05$ , \*\*\* $p \leq 0.01$



**Fig. 2** Expected difficulties in the future use of AI systems (n=91). The category ‘others’ includes barriers with less than five nominations. For a full list of all barrier reasons see the online supplementary material

## Discussion

In this study, a statistically significant influence of the *perceived ease of use* on the *acceptance of AI systems* is found. For this factor, the indicators of flexible and problem-free use of AI systems show the highest relevance. It can be concluded that flexibility in the operating process as well as a simple and trouble-free operation of AI systems are criteria that make AI systems appear more user-friendly. Manufacturers could take up this issue to develop user-friendly AI machines. Furthermore, a higher *perceived ease of use* leads to a higher *perceived usefulness* such as improvements in completing farm related tasks. The second factor of the TAM, *perceived usefulness*, however, does not affect the *acceptance of AI systems* in this study. Probably, it is difficult for the respondents to assess the usefulness of AI machines on their farms as only few application-ready systems exist so far. However, Pierpaoli et al. (2013) emphasize the importance of these two factors for a successful introduction of PATs. Previous research on PATs shows that the *perceived ease of use* and the *perceived usefulness* have a significant effect on the behavioral intention (Aubert et al., 2012; Michels et al., 2020a; Toma et al., 2018). Due to the lack of significance of the *perceived usefulness* in this study, methodological errors such as operationalization failures or comprehensibility errors should be examined more closely in future research. This is especially relevant since a lack of usefulness cannot be compensated by user-friendliness (Davis, 1993).

Compared to all factors examined in this study, the *perceived behavioral control*, which includes estimations of self-confidence and the importance of using AI systems, has the most important influence on the *acceptance of AI systems*. However, this result must be treated with caution. Regarding the *perceived behavioral control*, Sok et al. (2020) note that it is difficult to determine the extent to which a person actually has control over the performance of a particular behavior in empirical studies. Therefore, this factor is often considered as an approximation of actual control. Furthermore, the analysis shows that farmers’ *personal attitude* towards AI systems is important for acceptance. The weights of the indicators show that *personal attitude* is particularly determined by one’s own interest in exploring technological developments for agriculture and the expected importance of sustainable agriculture through AI systems. The *perceived social norm* is measured by statements on politics and society but does not show a significant influence on the *acceptance of AI systems*. Nevertheless, the positive direction of the path coefficient shows that a

positive public discussion about AI and digitalization in agriculture could increase farmers' *acceptance of AI systems*. In line with this, a representative survey by Pfeiffer et al. (2021) shows that the population remains alienated from agriculture and currently has a low level of knowledge about modern production processes. Digital technologies are only evaluated positively among consumers after having received an explanation of their potential. In a media analysis for Germany, Mohr and Höhler (2020) conclude that the reporting on digitalization in agriculture in various national daily and weekly newspapers is mostly favorable. In addition, the *perceived social norm* captures a favorable evaluation of digitalization and technology in agriculture by politicians. Currently, projects on digitalization in agriculture are funded by the Ministry of Agriculture (see Federal Ministry of Food and Agriculture, 2019) and the Ministry of Economics. In January 2021, funding was announced for a cloud called Agri-Gaia, which aims to bring AI into concrete application in agriculture (Federal Ministry for Economic Affairs & Energy, 2021). However, it is unclear whether this indicates a pioneering role for Germany or rather represents an attempt to make up for a backward development. The extent to which public opinion on digitalization affects the attitudes and behavior of farmers should be investigated in further analyses.

Finally, in this study, a statistically significant influence of farmers' *innovativeness* on the *acceptance of AI systems* is not observed. Since studies on PATs (e.g., Aubert et al., 2012; Blasch et al., 2020; Michels et al., 2020b) show a significant influence of *innovativeness* on acceptance, it can be assumed that the non-existent influence could be due to the small sample size of this study. Furthermore, the analysis shows that, in order to increase the acceptance of farmers towards AI systems, farmers should have sovereignty over their business data which can be derived from the statistically significant influence of farmers' *expectation of property rights over business data* on the *acceptance of AI systems*. Farmers might be afraid of the development of data monopolistic practices and data-based market power on the part of suppliers. While the attribution of a property right over business data by lawmakers could mitigate these fears, it is questionable whether this is a desirable regulation. The existing uncertainty regarding the allocation of data sovereignty for business data as well as the legal view on data sovereignty should be considered. Contractual agreements and voluntary self-commitments regulated in a code of conduct could initially help to establish a defined status quo (Vogel, 2020).

However, some limitations in the study design must be pointed out. First, the study is not based on a representative sample of German farmers in terms of age, region, farm size, or farm type. In this study, the farmers are comparatively young, predominantly male, and cultivate rather large areas of farm land. Previous studies have already shown that younger farmers are more likely to adopt PATs and that the farm size positively affects the adoption of PATs (e.g., Blasch et al., 2020; Groher et al., 2020; Vecchio et al., 2020). No influence was found for gender (e.g., Michels et al. 2020b; Paustian & Theuvsen, 2017). It can therefore be assumed that the farmers surveyed in this study are more inclined to use AI systems and the results might be overestimated. Thus, it is difficult to generalize the results of this study for German agriculture. Second, due to difficulties of addressing a large number of farmers without social media channels, the sample size is rather small, yet sufficient for the model estimation. Notwithstanding the relatively limited sample, this work offers valuable insights into preliminary key variables for AI acceptance in agriculture. A third limitation is the mixed survey approach. However, by characterizing the socio-demographics of both samples and reporting the response behavior for each group, this study aims to be as transparent as possible with respect to its participants. In order to meet SEM's quality criteria, the estimation of two separate models with the two samples is not performed. In line with the suggestions by Groher et al. (2020), future research could use the results and measurement instruments of

this study to develop a more detailed and possibly representative survey to identify additional drivers and barriers to AI acceptance.

Furthermore, it should be mentioned that the acceptance of AI systems does not automatically represent or predict the actual use of a technology. The actual use has not been investigated in this study since only few market-ready AI systems are currently available. In most cases, AI systems for agriculture are prototypes that are developed and tested by startups and research institutes (Partel et al., 2019). The existence of an intention-behavior gap should be considered as well. It cannot be completely ruled out that farmers may show a willingness to use AI systems, but that actual use will not occur once market-ready systems are established. In addition, it should be noted that some researchers point to difficulties in using the TPB as a theoretical framework for research on behavioral change (e.g., Sniehotta et al., 2014; Sok et al., 2020). However, to gain comprehensive insights into the factors influencing the *acceptance of AI systems* in agriculture, a composite model was chosen. Nevertheless, there are further influencing factors on acceptance that were not examined in this study such as the costs of AI systems. This study refrains from examining costs as an influencing factor on acceptance, because costs are not considered as a behavioral factor. However, it is very likely that the expected costs (e.g., acquisition, maintenance) have an important influence on acceptance as in the case for adoption of PATs (e.g., Blasch et al., 2020; Long et al., 2016; Lowenberg-DeBoer et al., 2020; Pierpaoli et al., 2013; Talaviya et al., 2020; Toma et al., 2018). Another non-behavioral influencing factor could be the missing robustness of technical systems. Both of these factors are stood out in the exploratory analysis (see results section) which is why the results of the exploratory approach (see Fig. 2) could be used to investigate the influence of further barriers on the *acceptance of AI systems* in agriculture. Nevertheless, this analysis provides starting points to support the future use of AI systems in agriculture as well as to understand the behavior of the actors and to convince them. At the same time, strategies should be developed to communicate and illustrate the advantages of actually using AI systems in agriculture, such as saving operating resources or providing a better decision support.

## Conclusion

The main goal of the current study is to identify behavioral factors influencing the acceptance of AI system in agriculture based on a theoretical framework. Using Davis' (1989) TAM, Ajzen's (1991) TPB, and two additional factors, expectation of ownership of business data and personal innovativeness, the influence of seven behavioral factors on the acceptance of AI in agriculture is examined. Results show that the two factors of the TPB, perceived behavioral control and personal attitude of farmers, have the most important influence on the acceptance of AI in agriculture. A statistically significant influence is found for the TAM factor perceived ease of use, as well as for the factor expectation of property rights over business data. Accordingly, this study adds to the growing body of acceptance and adoption research in agriculture with the difference of focusing on AI systems rather than on PATs. The identified motives and influencing factors can be used by politicians, manufacturers as well as by digital and agricultural associations to push digitalization in agriculture forward and thereby establish German agriculture as a pioneer in the field of digitalization and AI. It appears promising to inform stakeholders about the potential of digitalized agriculture, and farmers, in particular, should be involved in further developments.

## Appendix

See Tables 12 and 13.

**Table 12** Quality criteria of the reflectively measured models

Reflective Measurement Models	Indicator name	Indicator reliability Loadings ( $\geq 0.7$ )	Convergence validity AVE ( $\geq 0.5$ )	Internal consistency Pc ( $\geq 0.6$ )
<i>Acceptance of AI systems</i>	[A1]	0.888	0.739	0.850
	[A2] (R)	0.830		
<i>Personal innovativeness</i>	[PI1]	0.893	0.747	0.922
	[PI2]	0.896		
	[PI3]	0.833		
	[PI4]	0.832		
<i>Perceived usefulness</i>	[PU1]	0.763	0.632	0.872
	[PU2]	0.855		
	[PU3]	0.711		
	[PU4] (R)	0.843		

(R) denotes reverse coded data

**Table 13** Quality criteria of the formatively measured models

Formative measurement models	Indicator name	VIF ( $< 5$ )	Weight ( $\geq 0.1$ )	Loadings ( $> 0.5$ )
<i>Expectation of property rights over business data</i>	[BD1]	1.123	0.404*	0.284
	[BD2]	1.072	- 0.498*	- 0.266
	[BD3]	1.027	0.500**	0.478**
	[BD4]	1.165	0.624**	0.525**
	[BD5]	1.064	0.371*	0.503**
<i>Personal attitude</i>	[PA1]	1.466	0.115	0.525***
	[PA2]	1.575	0.208*	0.581***
	[PA3]	1.761	0.753***	0.946***
	[PA4]	2.182	0.135	0.786***
<i>Perceived social norm</i>	[PSN1]	1.018	0.433	0.545*
	[PSN2]	1.018	0.846***	0.903***
<i>Perceived ease of use</i>	[PEOU1]	2.033	- 0.256	0.440***
	[PEOU2]	1.699	0.435**	0.661***
	[PEOU3] (R)	1.042	0.383**	0.543***
	[PEOU4]	1.125	0.404***	0.625***
	[PEOU5] (R)	1.569	0.525***	0.694***
<i>Perceived behavioral control</i>	[PBC1] (R)	1.319	0.491***	0.813***
	[PBC2]	1.134	- 0.204**	- 0.505***
	[PBC3]	1.251	0.586***	0.849***

(R) denotes reverse coded data

\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$



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**Data availability** Excel-sheet available (author).

**Code availability** SmartPLS 3.

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