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Review

Adoption and diffusion of digital farming technologies - integrating farm-level evidence and system interaction

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ABSTRACT

CONTEXT: Adoption and diffusion of digital farming technologies are expected to help transform current agricultural systems towards sustainability. To enable and steer transformation we need to understand the mechanisms of adoption and diffusion holistically. Our current understanding is mainly informed by empirical farm-level adoption studies and by agent-based models simulating systemic diffusion mechanisms. These two approaches are weakly integrated.
OBJECTIVE: Our objective is to build an empirically grounded conceptual framework for adoption and diffusion of digital farming technologies by synthesizing literature on these alternative approaches.
METHODS: We review 32 empirical farm-level studies on the adoption of precision and digital farming technologies and 27 agent-based models on the diffusion of agricultural innovations. Empirical findings are synthesized in terms of significance and partially standardized coefficients, and diffusion studies are categorized by their approaches and theoretical frameworks.
RESULTS AND CONCLUSIONS: We show that farm-level studies focus on farm and operator characteristics but pay less attention to attributes of technology, interactions, institutional and psychological factors. Agent-based models, despite their usefulness for representing system interaction, only loosely connect with empirical farm-level findings. Based on the identified gaps, we develop a conceptual framework integrating farm-level evidence on adoption with a systemic perspective on technology diffusion.
SIGNIFICANCE: Our empirically grounded conceptual framework is the first holistic approach to connect the dots between the wealth of empirical research on technology adoption with more model-driven investigation of innovation diffusion in agent-based studies. Focusing on digital farming technologies, it may serve as a reference for those studying the adoption and diffusion of such technologies beyond farm scale. Furthermore, this framework can be the basis for contextual applications to inform policy-makers trying to foster the diffusion of suitable digital technologies through interventions as it highlights where policy can impact important aspects of adoption via relevant processes of diffusion.

1. Introduction

Digital farming has the potential to transform agricultural systems to be more sustainable by reducing the use of agrochemicals. Global agriculture faces various challenges to meet the demand for food and fibers in the coming years because it needs to maintain overall productivity without further polluting soil, water and other agroecological systems (Finger et al., 2019; Cole et al., 2018). Digital farming (also referred to as smart farming or agriculture 4.0) is expected to address these challenges using information communication technologies to collect and analyze data to support efficient farming processes (OECD, 2019; Bacco et al., 2019). Digital farming technologies cover a broad spectrum, from small mobile apps for decision support, over in-field sensors and remote sensing technologies for data collection, and to drones and robots for the automation of processes (see OECD (2019) for detailed categories of digital farming technologies). A sustainable agriculture in the future will need digital farming technologies (Walter et al., 2017), which use Artificial Intelligence (AI), cloud computing, Internet of Things (IoT), and blockchain among others (Torky and Hassanein, 2020; Klerkx et al., 2019). The rise of these technologies and the potential disruptive impact

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of digital agriculture make it particularly important to understand the mechanisms of adoption and diffusion of digital farming technologies.

The mechanisms of adoption and diffusion of digital farming technologies must be understood on both farm and system level, where system refers to the collection and organization of entities relevant for the adoption and diffusion. Adoption behavior not only depends on farm and operator characteristics but is also influenced by structural, political and economic conditions of the agricultural system. The system evolves over time, based on the behavior of the farmers and their interactions with their environment and one another (Alexander et al., 2013). It is the system interaction in combination with, and depending on, individual farm characteristics that will ultimately determine technology diffusion and its impact on the sustainability of agriculture. Therefore, it is necessary to understand not only individual adoption but also system interaction in the process of adoption and diffusion.

So far, our understanding of the mechanisms of technology adoption and diffusion mainly comes from separate empirical farm-level studies on individual adoption and agent-based models (ABMs) simulating systemic diffusion mechanisms. Other equally important system approaches like system dynamics (Reinker and Gralla, 2018) are beyond the scope of this paper. Farm-level adoption studies of digital farming technologies start to emerge in recent years, like Michels et al. (2020), Salimi et al. (2020), Caffaro and Cavallo (2019), Drewry et al. (2019), Pivoto et al. (2019), and Zheng et al. (2018), but they are still few compared to the large amount of adoption studies of other agricultural practices (e.g. sustainable farming practice (Dessart et al., 2019) and precision farming (Pathak et al., 2019)). This lack of information requires us to also refer to the lessons of precursor technologies, i.e. precision agriculture technologies (PATs). Farm-level adoption studies usually use regression-type analysis (e.g. logit, probit, poisson models) testing the effect of different variables on adoption (such as farm size and farmers' age) or qualitative descriptive approaches (e.g. descriptive summary of interviews with farmers) testing less measurable factor (such as compatibility of a technology and data safety) (Klerkx et al., 2019). These studies usually do not consider system interaction. When considering the process of adopting a potentially transformative technology like digital farming, feedback processes may speed up or dampen the technology diffusion. This requires us to look at mechanisms and models beyond the farm level.

ABMs are gaining popularity in modeling adoption and diffusion of innovations as they capture system interaction among heterogenous entities (Zhang and Vorobeychik, 2019). In an ABM, a system is modeled as a collection of autonomous decision-making entities, i.e. agents (Bonabeau, 2002). An agent can be an individual (e.g. a farmer) or a collective entity (e.g. an organization). It assesses its environment and behaves based on rules defined by modelers. ABMs enable researchers to create, analyze and experiment with models composed of agents that interact with each other and with their environment (Gilbert, 2007). Nevertheless, our review on ABMs of agricultural innovations (see section 3) shows that existing ABMs have not covered adoption and diffusion of digital farming technologies yet. Most importantly, we find that current ABMs are not well connected with empirical farm-level evidence on the adoption and diffusion of digital farming and are thus lacking the empirical foundation needed for applications beyond the toy-model stage so far (Matthews et al., 2007).

The objective of this paper is to build an empirically grounded conceptual framework for modeling adoption and diffusion of digital farming technologies. To this end, we synthesize literature from empirical farm-level adoption studies of precision and digital farming technologies with ABMs simulating systemic diffusion mechanisms. We need to establish this connection to later explore how farmers' (adoption) behavior influences the system and how changed system conditions in turn affect what is happening at the farms. This dynamic and spatially differentiated process ultimately determine diffusion of digital farming technologies, and understanding them could help us to identify effective pathways for sustainable agricultural systems. Such a conceptual framework can be the basis for contextual applications to inform policy-makers trying to foster implementation of suitable digital technologies through interventions, such as subsidies and extension services. Our empirically grounded conceptual framework may generally serve as a reference for those studying the adoption and diffusion of digital farming technologies beyond farm scale, and it may more specifically interest ABM modelers aiming to simulate such processes in different contexts. The results of structured – and in parts quantitative – review of both strands of literature are by themselves relevant contributions for the respective communities.

This paper is organized as follows. In section 2, we review farm-level adoption studies of precision and digital farming technologies and summarize determinants of farmers' adoption decisions. In section 3, we review ABMs of adoption and diffusion of agricultural innovations and their limitations for modeling adoption and diffusion of digital farming technologies. Section 4 presents the empirically grounded conceptual framework for modeling adoption and diffusion of digital farming technologies. Section 5 concludes the paper and points out its limitations and directions for future research.

Table 1
Search terms used and number of farm-level studies identified.

Group	Search terms	Number of studies
1	TS = (agricultur* OR farm*) AND TS = (technolog* OR innovation*) AND TS = (adopt* OR diffusion)	6694
2	TS = (precision OR digital OR "smart farming" OR robot* OR autonomous OR automa* OR "unmanned aerial vehicle*" OR drone OR "cloud computing" OR "site specific" OR "variable rate" OR "GPS" OR "remote sensing" OR "soil sampling" OR "yield mapping" OR "yield monitor*" OR "autosteer" OR drip OR irrigation OR water saving)	1,389,788
	Combine 1 and 2 (by logical "AND")	1266

Source: own results.
Note: TS = Topics, referring to the title, abstract, or keywords of an article.

2. Empirical farm-level studies of technology adoption

2.1. Selection of farm-level studies

The literature search was conducted a final time on 14 April 2020 using the Web of Science database. Search terms used and numbers of studies identified are presented in Table 1. Search terms of group 1 require that studies must investigate adoption or diffusion of agricultural technologies/innovations. Group 2 requires that the investigated technologies must be either precision or digital (including autonomous) farming technologies. The combination of group 1 and 2 (by logical "AND") resulted in 1266 identified studies.

After reading all 1266 abstracts, we selected 32 studies that focus on determinants of farmers' decision to adopt technologies in crop production (see Appendix 1). We only focus on crop production because only two studies of livestock production (Abeni et al., 2019; Lima et al., 2018) are found by the structured literature search. Nearly half of the selected studies (14) was conducted in the USA; 12 studies in European countries; and the rest in Canada (2), Australia (1), Brazil (1), China (1),

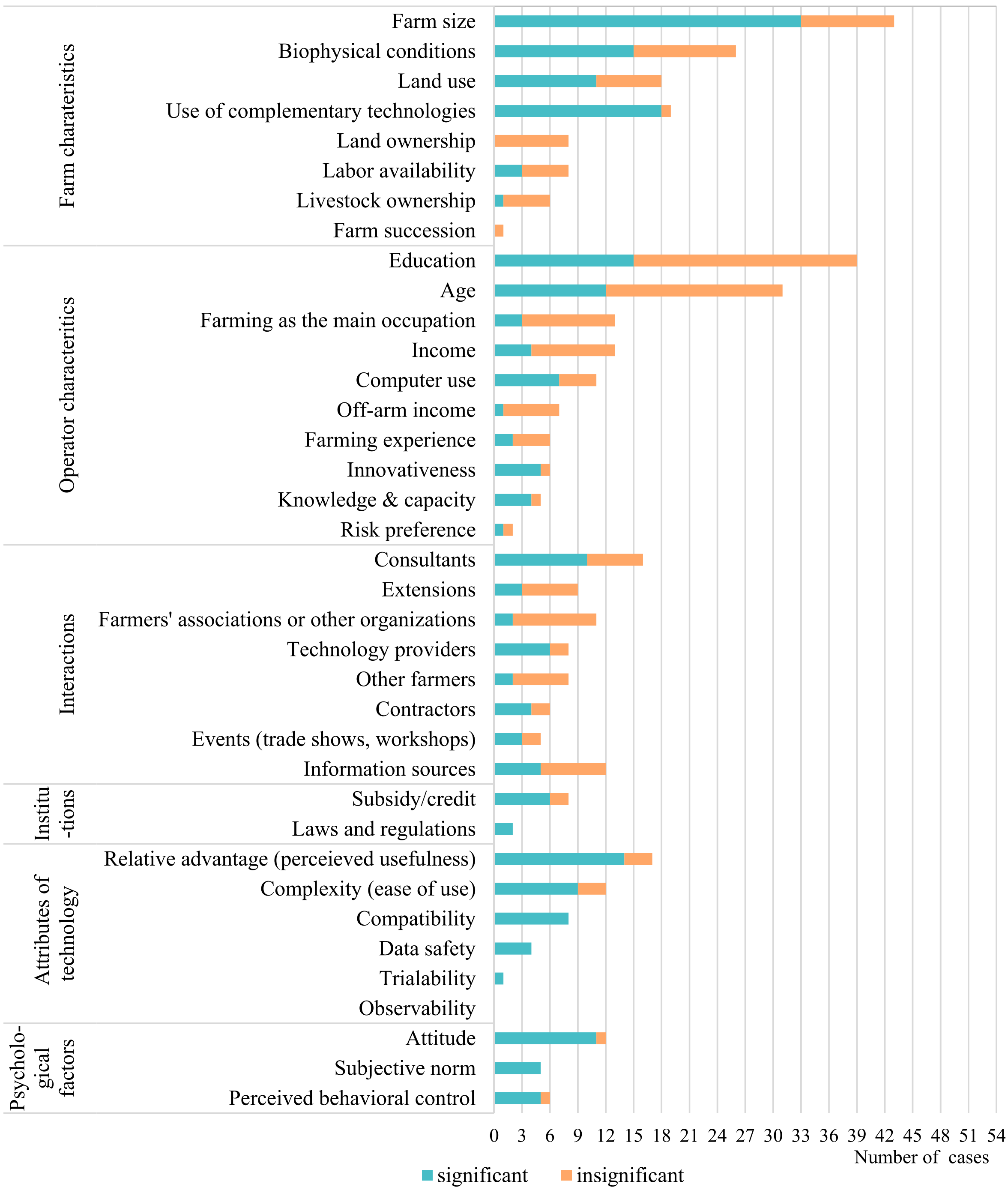

Fig. 1. Influencing factors on farmers' technology adoption decision synthesized from 54 cases.
(Source: own results)

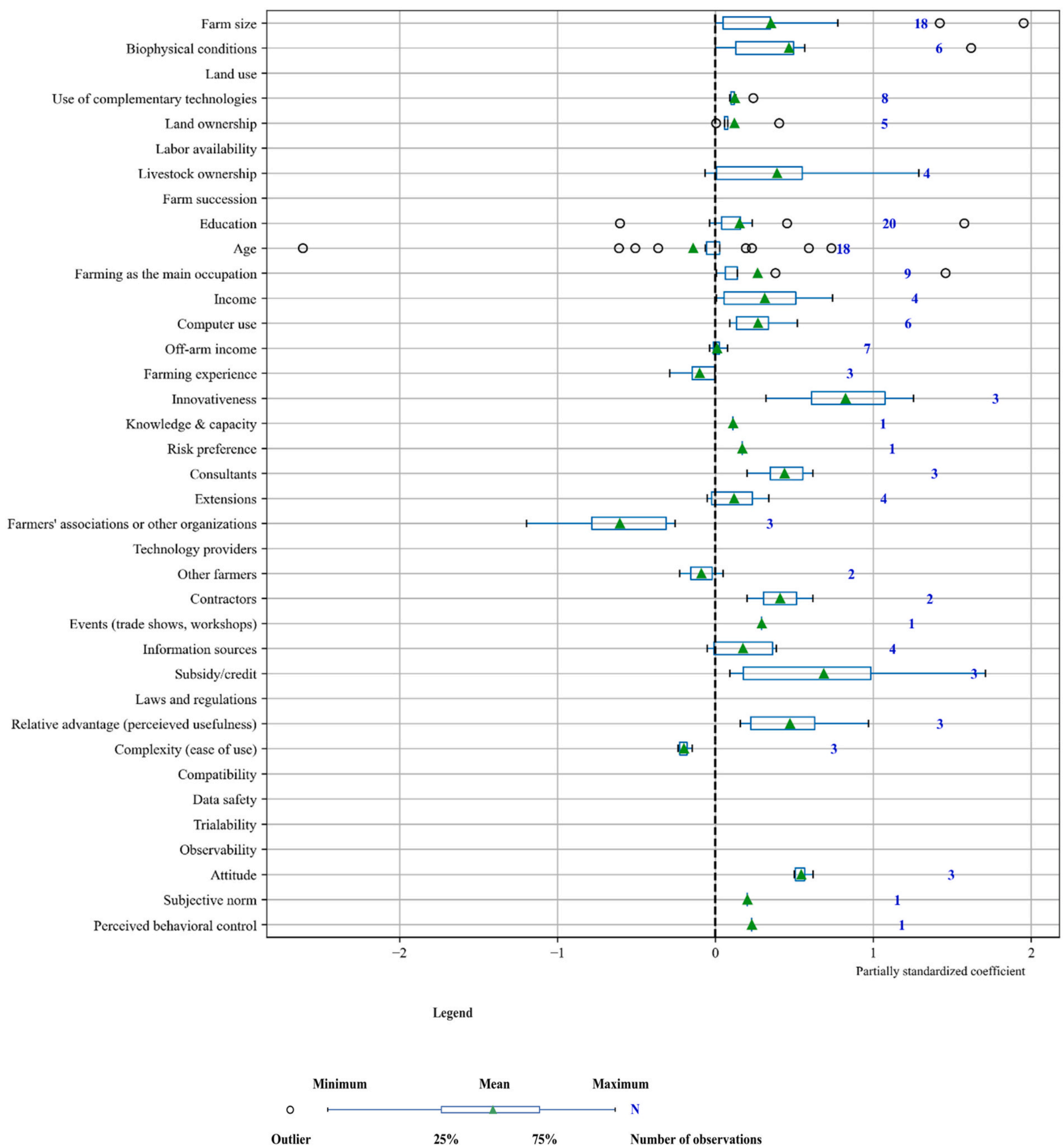

Fig. 2. Partially standardized coefficients of factors from models with binary outcome.
(Source: own results)

and Iran (1). In terms of methods, 26 studies used regression-type analysis (e.g. logit, probit, poisson models), and 6 studies used qualitative descriptive approaches (like descriptive summary of interviews with farmers or experts). Among regression-type studies, 21 studies modeled the adoption decision as a binary outcome (yes/no), and 8 studies modeled intensity of adoption (e.g. number of PATs used). Some studies included both cases, and some regression-type studies also included qualitative descriptions.

In this study, we consider not only the significance of factors but also their importance for explaining adoption. Fig. 1 illustrates the frequencies with which factors are considered and identified as significant (significant at least at a 10% level if it is a regression-type analysis; identified as important if it uses qualitative approach) or as insignificant. Some studies modeled the binary adoption decision and adoption intensity of multiple technologies. Thus, we count the number of cases (in total 54 cases reported in 32 studies, as shown in x-axis of Fig. 1) instead of the number of studies. Factors are grouped into 6 categories: farm characteristics (e.g. farm size), operator characteristics (e.g. age of the operator), interactions (e.g. get information from consultants), institutions (e.g. regulations), attributes of technology (e.g. relative advantage) and psychological factors (e.g. attitude towards the technology). Fig. 2 summarizes partially standardized coefficients of factors representing their importance (i.e. effect size) in farmers' adoption decisions.

2.2. Significance of factors

2.2.1. Farm characteristics

Farm characteristics get a great deal of attention in farm-level studies. 1) **Farm size** is identified to be positively related to adoption in 33 out of 43 cases. Large farms can take advantage of economies of scale and are more likely to be able to afford the high initial investment of new technologies (Tamirat et al., 2017). One may speculate that large farms are more targeted by technology providers for their potential of a higher sales volume. 2) **Biophysical conditions** like yield variability and locations are found significant by 15 out of 26 cases. Farmers with higher quality land might anticipate greater potential benefits from adoption than farmers with lower quality land (Isgin et al., 2008). 3) **Land use** like the share of arable land or share of a certain crop determines if the technology meets the farms' needs and is found relevant by 11 out of 18 cases. Barnes et al. (2019) find that farms with a high share of arable land tend to adopt more PATs. Paustian and Theuvsen (2017) find producing barley negatively influences the adoption of PATs. 4) **Use of complementary technologies** positively contributes to the adoption of other PATs as shown in 18 out 19 cases. For instance, farmers who already use a variable rate technology are more likely to adopt yield mapping technologies (Isgin et al., 2008). 5) **Land ownership** might influence the adoption of technologies requiring investments tied to the land such as precision irrigation (Moreno and Sunding, 2005; Abdulai et al., 2011). However, none of the 8 cases that include this as an explanatory variable find it statistically significant. 6) **Labor availability** like the number of regular employees is statistically significant in 3 out of 8 cases. Pivoto et al. (2019) find that the lack of skilled labor operating the new technology is a constraint for the adoption. On the other hand, labor availability and cost could be the main drivers of robotic farming technologies. 7) **Livestock ownership** is considered in 6 out of 54 cases, but only Lambert et al. (2015) find a positive relationship between owning livestock and adoption of computerized cotton management system with digital maps. 8) **Farm succession** could be an important factor influencing farmers' adoption decision in digital farming technologies that require high investment, but only Paustian and Theuvsen (2017) consider this factor and find it statistically insignificant.

2.2.2. Operator characteristics

Features of farm operators are often researched in farm-level studies. 1) **Education** level is found significant in 15 out of 39 cases. Farmers with a high level of education could better comprehend the application of new technologies (Aubert et al., 2012). 2) **Age** is found significant in 12 out of 31 cases, and 11 cases report a negative impact of age on adoption. The complexity of digital farming technologies is perceived as a barrier to adoption for older farmers. Moreover, fewer working years until retirement reduces the planning horizon regarding technology use (Barnes et al., 2019). However, Pivoto et al. (2019) observe that older farmers tend to adopt autopilot spraying. 3) **Farming as the main occupation** is reported to be significant in 3 out of 13 cases. The more important the farm to the household, the higher the willingness to adopt (Zheng et al., 2018). 4) **Income** impacts adoption as shown in 4 out of 13 cases. This might be due to high initial investments required by digital farming technologies. 5) **Computer use** for farm management is examined by 11 cases and 7 of them observe a positive impact on adoption. Being familiar with computers makes farmers comfortable in using PATs (D'Antoni et al., 2012). 6) **Off-farm income** is only found significant by Schimmelpfennig and Ebel (2016) in the case of adoption of a bundle of technologies (yield monitor, GPS and variable-rate technologies). 7) **Farming experience** (in years) is explored by 6 cases but only 2 cases imply a positive impact (Asare and Segarra, 2018; Paustian and Theuvsen, 2017). 8) **Innovativeness** of a farmer is found significant for adoption by 5 of 6 cases (e.g. Pino et al., 2017; Aubert et al., 2012). 9) **Knowledge & capacity** are crucial as 4 out of 5 cases point out. Lack of knowledge in new technologies (especially in software and data transfer) is a barrier to adoption (Takácsné György et al., 2018). 10) **Risk preference** has been rarely investigated (2 out of 54 cases). Farmers with a higher ratio of debt to asset (a proxy of risk preference) tend to adopt more PATs (Isgin et al., 2008).

2.2.3. Interactions

Although interactions within social networks are found influential for adoption of agricultural innovations (Ramirez, 2013; Sampson and Perry, 2019), they have not become a focus of adoption studies of precision and digital farming technologies (Fig. 1). 1) Having **consultants** is found by 10 out of 16 cases to be significantly associated with adoption. Lack of advisory services and the negative opinion on PATs from advisors influence farmers' adoption decisions (Pivoto et al., 2019). 2) **Extensions** connect researchers and farmers by introducing innovations to farmers, and they are found to be influential by 3 out of 9 cases. Asare and Segarra (2018) report a negative impact of having contact with university extensions on adoption of soil sampling technology, while in Larson et al. (2008) farmers who believe that information from extensions are helpful tend to be adopters of remote sensing technology. The interview of Kutter et al. (2011) considers private extension service the most important promoter of PATs. 3) **Farmers' associations or other organizations** are often believed to be an information source for farmers, but only 2 of 11 cases affirm their impact on farmers' adoption decisions (Barnes et al., 2019; Takácsné György et al., 2018). 4) **Technology providers** offer farmers pre-adoption trials and training, farm system advice and post-installation technical support. More technical support and training from technology providers are believed to promote adoption (Drewry et al., 2019; Barnes et al., 2019). 6 out of 8 cases find a positive effect of having access to technical support and training from technology providers on farmers' adoption decisions. 5) **Other farmers** can influence farmers' decisions through information exchange.

However, the 6 regression-type studies we reviewed have not found the statistical significance of exchanging information with other farmers. But the interviews conducted by Pivoto et al. (2019) and Kutter et al. (2011) emphasize the impact of neighbors' negative opinions on PATs and the importance of obtaining information from other farmers. 6) **Contractors** provide machinery services to farmers. 4 out of 6 cases emphasize the impact of getting information from contractors or paying them for related farming activities (e.g. Gallardo et al., 2019; Larson et al., 2008). Especially for small farms, contractors will be a major driver behind the adoption (Kutter et al., 2011). 7) Attending **Events** (trade shows, workshops) is identified as influential by Lambert et al. (2014), Tamirat et al. (2017) and Kutter et al. (2011). 8) **Information sources** in general play a role in farmers' adoption decisions as shown in 5 out of 12 cases.

2.2.4. Institutions

Institutions are "the rules of the game in a society" (North, 1990, p.3) and devise constraints that shape human interactions. They consist of formal and informal rules, norms, beliefs, and potentially organizations. Institutional theories are expansive (see Ostrom, 2005), thus we only focus on what we found in the literature.1) Accessibility of **subsidy/credit** is believed to have a positive effect on adoption by 6 out of 8 cases. Reichardt and Jürgens (2009) point out that financial support is a prerequisite for diffusion of PATs. Lambert et al. (2015) discover that farmers who participate in conservation easement programs are more likely to adopt PATs. 2) **Laws and regulations:** 2 cases (Barnes et al., 2019; Kutter et al., 2011) find that increasing environmental requirements (e.g. stringent laws on pesticide and nitrogen application) are one of the forces for adoption of PATs that can significantly reduce chemical use. In the context of digital farming, regulations that ensure data ownership and prevent misuse of farms' data can promote adoption of digital farming technologies (Barnes et al., 2019).

2.2.5. Attributes of technology

Regarding attributes of technology, the theory of Diffusion of Innovation (DOI) of Rogers (2003) and the Technology Acceptance Model (TAM) of Davis (1985) are often applied by empirical studies. We organize attributes of technology according to the DOI because it covers a broader range than TAM. According to the DOI, the perceived attributes of an innovation (relative advantage, complexity, compatibility, trialability, and observability) are important explanations of adoption (Rogers, 2003). Surprisingly, they seem to be less researched regarding adoption of precision and digital farming technologies. 1) **Relative advantage** (perceived usefulness in TAM) like increasing productivity promotes adoption, while high cost and time required for handling data are barriers (Adrian et al., 2005). Only 10 out of 46 regression-type cases consider this attribute, and 7 cases identify it as significant (e.g. Walton et al., 2008; Zheng et al., 2018). Qualitative descriptive studies pay more attention to attributes of technology than regression-type studies. They explore the exact advantages and disadvantages of adopting precision and digital farming technologies. In 7 out of 8 descriptive cases, better information for farm management, reduction in input-use, and high yield are the most often mentioned motivations for farmers to adopt such technologies. "High initial investment" and "time consuming" are the two most often mentioned disadvantages (Reichardt and Jürgens, 2009). 2) **Complexity** (perceived ease of use in TAM) was considered by 12 cases. Studies using interviews with farmers and experts convey that complexity in manipulating data and machines is a constraint for adoption (Pivoto et al., 2019). 3) **Compatibility** of new farming technologies to existing machinery, poor telecommunication infrastructure and data interoperability are constraints of adoption of precision and digital farming technologies, pointed out by 7 qualitative cases, while only 1 regression-type analysis considers this attribute (Aubert et al., 2012). 4) **Trialability** actualized in a positive exploratory experience can facilitate the adoption. However, the only study that considers this attribute (Aubert et al., 2012) reveals a negative relationship between trialability and adoption. As they interpret, this might be because non-adopters have a too optimistic prior impression about the ease of use of new technologies. 5) **Observability** of the technology by peers is not examined by any of the studies we have reviewed. This constitutes stark negligence of its stated importance for adoption in the DOI. 6) We add a sixth attribute, **data safety**, which is especially relevant for digital farming. Issues of data safety have been stressed by 4 descriptive cases (Drewry et al., 2019; Kutter et al., 2011; Pivoto et al., 2019; Reichardt and Jürgens, 2009). They stress that concern about the misuse of digital data by commercial service providers makes farmers more cautious. Besides the papers we reviewed, recent studies (e.g. Pfeiffer et al., 2020; Wiseman et al., 2019; Klerkx et al., 2019) highlight the urgent need for legal and regulatory frameworks of data collection and use in the context of digital farming.

2.2.6. Psychological factors

Psychological factors are less investigated by models with binary outcomes and interviews, but more by models of adoption intensity. The Theory of Planned Behavior (TPB), developed by Ajzen (1991), is a theoretical framework often used in examining the impacts of farmers' perceptions on technology adoption. The TPB states that a person's intention to do something is determined by his or her attitude, subjective norm and perceived behavioral control. 1) **Attitude** is a farmer's positive or negative evaluation of adoption. It is found to be statistically significant in 10 out of 12 cases. Farmers who believe the technology is beneficial tend to adopt it (Pino et al., 2017). 2) **Subjective norm** refers to the perceived pressure or expectation to adopt or not. 5 cases find that external pressure from the community and environmental organizations positively contributes to adoption of PATs (e.g. Aubert et al., 2012; Lynne et al., 1995). 3) **Perceived behavioral control** refers to a farmer's perceived ability to implement adoption. It contains self-efficacy and perceived controllability (Ajzen, 2002). 5 out of 6 cases confirm the importance of this factor. Lynne et al. (1995) declare a positive relationship between perceived behavioral control and technology adoption, while Pino et al. (2017) do not.

2.3. Importance of determinants

Statistical significance of an explanatory factor neither tells anything about the size of the effect per unit change nor about the variability of variables in the data. Both are crucial elements to assess the *importance* of the effect for explaining adoption. As a consequence, we calculated the partially standardized coefficient of each factor from regression models. Standardized coefficients make it more meaningful to compare the relative influence of different independent variables on the dependent variable when these variables are measured in different scales or ways. Standardized coefficients transform the independent variables into variables measured in "standard deviation units" (sd_x) (Menard, 2004). However, calculating standardized coefficients also requires knowing the standard deviation of dependent variables (sd_y). In the case of logit models, standard deviation of transformed dependent variables using logit link ($sd_{logit(y)}$) is required (Menard, 2004), which can be calculated when pseudo R-squared and $sd_{logit(\hat{y})}$ are available. Given the limited data availability, we use partially standardized coefficients. They allow us to compare the importance of different independent variables assuming that the variances of the dependent variables from different models are similar. Following Agresti (2007), we calculate a partially standardized coefficient of an independent variable as:

$$\beta_x = b_x * sd_x,$$

where b_x is the non-standardized coefficient of the independent variable x; sd_x is the standard deviation of the independent variable x.

The interpretation of a partially standardized coefficient, β_x, is that if the independent variable x increases by one standard deviation unit (sd_x), the dependent variable (y) or the transformed dependent variable using a logit or probit function (*logit*(y), *probit*(y)) will increase by β_x unit (s).

A boxplot (Fig. 2) presents partially standardized coefficients of independent variables in models with binary outcomes[1] (i.e. adopt or not adopt) following the same categorization from section 2.1.

The boxplot in Fig. 2 shows the minimum, maximum, first quartile, third quartile, mean, outliers, and the number of observations. The higher the number of observations (i.e. cases in this study), the more reliable the means of the partially standardized coefficients are. Thus, we try to interpret the results in the sequence of the reliability of the synthesized data and by the comparability of factors. Note that although some factors have no observations that enable us to calculate the partially standardized coefficients, they are not omitted in Fig. 2 to keep the consistency with Fig. 1. Another advantage of presenting all factors is that the unexplored factors can highlight potential directions for future research.

Among the most investigated factors i.e. farm size (18 observations), education (20 observations) and age (18 observations), the partially standardized coefficients of farm size have a higher mean value (0.35) than education (0.15) and age (−0.13). This implies that an increase by a standard deviation unit in farm size influences farmers' adoption decision more than that of education and age. Besides, farm size is consistently shown to have positive partially standardized coefficients, which means larger farms are more likely to adopt new technologies. Education also shows relatively consistent positive impacts with four exceptions. Age, on the contrary, does not seem to be a helpful predictor for adoption because of its varying and inconsistent pattern.

For biophysical conditions, we calculated the partially standardized coefficients of "yield" (6 observations, mean = 0.47). A change of one standard deviation unit in yield is shown to have a bigger impact on adoption than that of land ownership (5 observations, mean = 0.12) and farming as the main occupation (9 observations, mean = 0.27). Off-farm income (7 observations, mean = 0.01) is shown to have a smaller impact on adoption than total income (4 observations, mean = 0.31). Use of complementary technologies (8 observations, mean = 0.12) and computer use (6 observations, mean = 0.27) both have positive impacts on farmers' adoption decisions, with the latter showing overall larger importance.

Regarding attributes of technology, partially standardized coefficients of "perceived usefulness" (3 observations, mean = 0.47) and "complexity" (3 observations, mean = −0.20) were calculated. Together with attitude (3 observations, mean = 0.54), the importance of these three factors and their consistency remind us that attributes of technology and farmers' attitude towards the technology have the potential to be more useful predictors for adoption decisions than characteristics of farms and farmers. From the higher numbers of observations from farm and operator characteristics, we can see that adoption studies in the past have been focusing on social-demographics, while overlooking the importance of attributes of technology and psychological factors. Given the limited information, we do not discuss other factors any further but leave them for inspection by readers.

As we mentioned in section 2.2, the significance of interactions within social networks has not been investigated as often as one would expect according to researchers like Rogers (2003), Ramirez (2013), and Sampson and Perry (2019). In terms of their importance, surprisingly, interaction with other farmers seems less important for adoption than most of the other factors at first sight, but the evidence on this is very limited (2 observations, mean = −0.09). We also notice that interaction with other farmers can negatively impact a farmer's adoption decision (Pivoto et al., 2019). A possible interpretation is that this can happen when the attitude of other farmers towards the new technology is negative as negative opinions can diffuse in social networks as well (Deffuant, 2006). This highlights the role of social norms and their dissemination in farmers' adoption decision. In further investigations, we combined the search term of TS = ("social network analysis") with group 1 and 2 (Table 1), but no adoption studies of precision or digital farming technologies yet using the method "social network analysis" were found in the Web of Science.

[1] Synthesized partially standardized coefficients of independent variables in models of adoption intensity are shown in Appendix 2. We don't include them in the main text due to limited observations.

Table 2
Search terms used and number of ABM studies identified.

Group	Search terms	Number of studies
1	TS = ("agent-based" OR "agent based" OR "abm" OR "multi-agent" OR "multi agent") AND TS = (adopt* OR diffusion OR innovati* OR technolog*)	5129
2	TS = ("agent-based" OR "agent based" OR "abm" OR "multi-agent" OR "multi agent") AND TS = (agricultur* OR farm* OR water OR crop)	1293
	Combine 1 and 2 (by logical "AND")	265

Source: own results.
Note: TS = Topics, referring to the title, abstract, or keywords of an article.

2.4. Limitations of farm-level studies

When considering the process of adopting digital farming technologies, which potentially can transform the agricultural system, factors determining each farmer's adoption decision change over time and across space. Farmers may learn about the technology from neighbors who already adopted it. This means farmers' awareness, knowledge and attitude may keep changing during the diffusion process of a new technology. Technology suppliers can offer more mature and/or cheaper versions based on feedback from users and economies of scale. Additionally, farmers may get more or better services by outsourcing technology implementation as the technology is spreading over time (Pedersen et al., 2020). Thus, feedback processes may speed up or dampen technology diffusion. However, as presented above, farm-level studies of complex technologies often assume variables to be exogenous and do not capture the interrelationship among variables. Thus, they do not account for the effects of endogenous feedback within a system. Consequently, the understanding of the processes leading to the diffusion of a new technology in the farm population requires us to look at mechanisms and models beyond the farm level.

3. ABMs of adoption and diffusion of agricultural innovations

As mentioned in the introduction, ABMs are gaining popularity in modeling adoption and diffusion of innovations as they capture system interaction among heterogenous entities in a temporal explicit manner (Zhang and Vorobeychik, 2019). For example, farmers (one type of agents) in Sun and Müller (2012) decide whether to convert cropland to forest (in response to a payment for ecosystem services) or not, based on not only their socioeconomic characteristics and features of their land but also on other farmers' behavior. Once farmers have made their decision, macro-level phenomena (e.g. total amount of area converted by all villagers in this case) can be perceived by farmers. Those in return may influence farmers' decisions for the next simulation period (time-step), thus new macro-level phenomena emerge thereafter (Galán et al., 2009).

ABMs can easily model peer interaction as one of the central elements in the theory of DOI, which is rarely considered by farm-level studies as shown in Fig. 1. ABMs have been used in various research fields such as geography, urbanization, agricultural land-use and political science, etc. (Gilbert, 2007). In the field of agricultural economics, ABMs are used in modeling farmers' decisions on crop selection, use of natural resources, adoption and diffusion of innovations, etc. (see a review of Kremmydas et al., 2018). In this section, we will explore factors

Fig. 3. Factors influencing adoption and adoption models in ABMs of agricultural innovations. (Source: own results)

that are considered in current ABMs of agricultural innovations.

3.1. Selection of ABM studies

The literature research was conducted a final time on 05 May 2020 using the Web of Science database. Search terms used and numbers of studies identified are presented in Table 2. Search terms of group 1 require that ABM studies must investigate adoption or diffusion of technologies/innovations. Group 2 requires that ABM studies must be agriculture-related. So far, no ABMs of adoption and diffusion of precision or digital farming technologies are found. Thus, we did not limit our scope to this but also included other innovations (e.g. new practices, crops, etc.) to get a better picture of farmers' decision-making strategies of adoption and their limitations in current ABMs. The knowledge from farm-level adoption studies of precision and digital farming technologies and the knowledge from ABMs of diffusion of agricultural innovations are then combined to build the conceptual framework.

The combination of group 1 and 2 (by logical "AND") resulted in 265 identified studies. After reading all 265 abstracts, we selected only 27 ABM studies (Fig. 3) that explicitly modeled adoption or diffusion of agricultural innovations. The innovations covered by these studies include conservation practices and programs (8 studies, e.g. Sun and Müller, 2012), innovative crops (7 studies, e.g. Alexander et al., 2013), innovative farming systems like organic farming and multifunctional agriculture (6 studies, e.g. Kaufmann et al., 2009), irrigation technologies (5 studies, e.g. Berger, 2001), fertilizers (2 studies, e.g. Beretta et al., 2018), and others. Note that the number of studies across all categories exceeds 27 because some articles include multiple innovations and are therefore counted as multiple times.

3.2. Factors influencing adoption and adoption models in selected ABMs

To compare factors considered in ABMs and in farm-level studies, we keep using the six categories summarized from empirical farm-level studies (see section 2), but replace "information sources" with "other types of agents" in the category "interactions" to better fit the structure of ABMs. Fig. 3 shows factors that directly affect the adoption decision process (i.e. triggers) and factors considered elsewhere (i.e. indirect factors) in the model, as well as the farmers' adoption model of each ABM. Modeled factors including triggers and indirect factors are to a large extent influenced by the adoption model applied by each study. In Fig. 3, studies are ordered according to the similarity of their adoption models, so that the advantages and limitations of each type of adoption behavioral model can be clearly illustrated.

Pure economic models (Ng et al., 2011; Sorda et al., 2013; Bell et al., 2016) usually depend on data of farm characteristics to maximize farmers' profit or utility. This type of model has one trigger for adoption i.e. profit/utility (marked at relative advantage in the category of "attributes of technology") and ignores other aspects. Some studies (Berger, 2001; Berger et al., 2007; Carauta et al., 2018; Schreinemachers et al., 2007, 2010) combine economic models with the threshold model, which divides farmers into Rogers' five adopter groups (innovators, early adopters, early majority, late majority, and laggards) with percentages that work as "adoption thresholds" mimicking a contagion process (Rogers, 2003). Although this type of model allows for farmers' innovativeness triggering adoption in addition to economic determinants, it does not explicitly model direct interactions of farmers. Seven studies (Alexander et al., 2013, 2015; Cai and Xiong, 2017; Huang et al., 2016; Manson et al., 2016; Olabisi et al., 2015; Perello-Moragues et al., 2019) explicitly model the effects of neighbors' information or opinion on the adoption decision of a farmer as well as economic determinants. Farmers' psychological factors are usually investigated by cognitive models. Four studies (Kaufmann et al., 2009; Van Oel et al., 2019; Xu et al., 2018, 2020) use cognitive models where farmers' psychological factors like attitude and subjective norms are the only triggers, while farm characteristics are to a great extent ignored. Two studies use the combination of economic and cognitive models (Brown et al., 2016; Chen et al., 2012). Typology models of Daloğlu et al. (2014a)[2] and Sengupta et al. (2005) assign a probability of adoption according to some features (including farm size, farm income, age of the operator, land ownership, labor availability, information sources, etc.) of the agent, thus allow multiple triggers from different categories for adoption. However, assigning the probability of adoption assumes farmers' adoption decision is independent from each other once farmers' features are determined. Farmers might be able to still interact in other parts of the simulation (e.g. on the land market), but their adoption decision would not be affected anymore by the others. The other four ABMs at the end of the list are less typical: Beretta et al. (2018) only model the impact of social networks on adoption based on the attributes of the low requirement for investment and knowledge about the innovation – new fertilizers; Holtz and Pahl-Wostl (2012) model diffusion on an aggregated level using the Bass Model (Bass, 1969), in which the more widespread the technology is, the higher the probability that a farmer considers this technology, without any farm characteristics; the ABM of Schreinemachers et al. (2009) contains an econometric model that captures the influence of farm and farmer' characteristics on adoption; and Sun and Müller (2012) integrate a machine learning algorithm into the ABM, while farmers' perception (e.g. attitude) and the effect of neighbors are also captured.

3.3. Limitations of ABM studies

As can be seen from the shading patterns in Fig. 3, the current ABMs of diffusion of agricultural innovations are only loosely connected to farm-level findings. Limitations are listed by the following four observations.

(1) Agent types and their interactions: most ABMs represent only a limited number of agent types. Other agent types highlighted in the theory of DOI (especially extensions and technology suppliers) are rarely considered. This is somewhat surprising given the general capacity of ABMs to explicitly model different agent types and heterogeneity within types (exceptions include Alexander et al., 2013 and Alexander et al., 2015; Sorda et al., 2013; Cai and Xiong, 2017; and Manson et al., 2016). Rounsevell et al. (2012) propose a notion of human functional types (HFTs), which define an agent by three dimensions (i.e. role, preference and decision-making strategies), to generalize representations of actors and support the expansion of ABMs. The advantages of applying HFTs are demonstrated by Arneth et al. (2014). For example, based on HFTs, Holzhauer et al. (2019) further demonstrate how institutional agents at global and regional scales can be modeled to study the impact of institutions on land use change. Similar approaches can be adopted by ABM modelers who aim to study the impact of interactions among different types of agents on technology adoption.

(2) Operator characteristics and psychological factors: ABMs lack the attention to farmers' ability and confidence to handle the complexity of new technologies with respect to the adoption decision that farm-level studies show (exceptions are Kaufmann et al., 2009; Sun and Müller, 2012; Schreinemachers et al., 2007 and Schreinemachers et al., 2009; Holtz and Pahl-Wostl, 2012). Likewise, considerations of substantial investments into complex technologies are bound to the current stage of farmers' life and farm succession, which can be well captured by ABMs, as the empirical findings regarding farmers' age showed. Due to the complexity and high requirement of investment of digital farming technologies, farmers' age, knowledge and self-efficacy[3] deserve more attention from ABMs.

(3) Attributes of technology: ABMs usually only consider the change in profit by adoption (relative advantage) and overlook other attributes of innovations, except for Olabisi et al. (2015). Since compatibility, complexity and issue of data safety are becoming concerns of farmers (Fig. 1), modelers could integrate these attributes of digital farming technology into ABMs by considering existing farm equipment, farmers' knowledge and capacity, and risk preference.

(4) Lack of consideration of institutions: ABMs have shown to be capable of explicitly modeling institutions like regulations (Ng et al., 2011), social norms (Kaufmann et al., 2009) and beliefs (Sun and Müller, 2012) that govern agents' behavior, but only a few studies have

[2] See also Daloğlu et al. (2014b).

[3] A review of non-agricultural related technology diffusion ABMs revealed that psychological factors like perceived behavioral control and self-efficacy were modeled more frequently in those models.

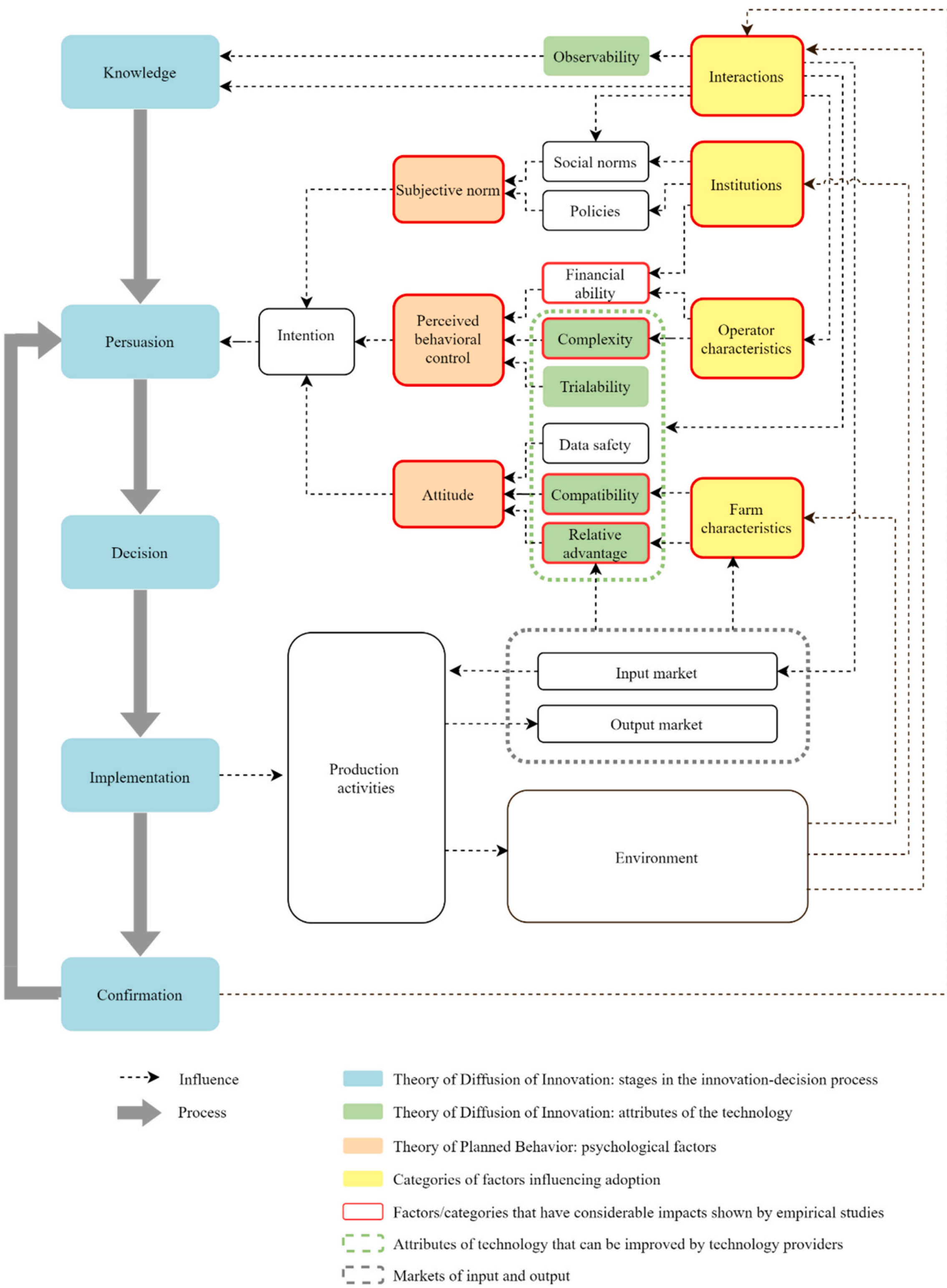

Fig. 4. Conceptual framework for empirically grounded ABMs of adoption and diffusion of digital farming technologies.
(Source: own illustration)

considered them as shown in Fig. 3. Here, the failure of ABMs to cover institutions does match the lack of attention of empirical studies, although regulations, laws and norms are influential for the acceptance of digital farming technologies (Barnes et al., 2019). Modeling institutional agents allows important research questions related to the impact of governance structures and policy formulation (Rounsevell et al., 2012) in determining the adoption and diffusion of digital farming technologies.

4. A conceptual framework for empirically grounded ABM

Having identified the loose ends of both strands of literature, we aim to build an empirically grounded conceptual framework for modeling adoption and diffusion of digital farming technologies of crop production. As suggested by Weersink and Fulton (2020), adoption should be understood as a process with multiple stages. We apply the model of five stages in the innovation-decision process from the theory of DOI (Rogers, 2003), i.e. knowledge, persuasion, decision, implementation and confirmation (see an example of Zheng and Jia, 2017). Because adoption of digital farming technologies is not a short-term commitment with potentially substantial changes in input use and farm management, a reasoned action approach is supposed to better capture farmers' decision mechanisms (Kaufmann et al., 2009). Thus, we apply the TPB to conceptualize intention formation due to its success on predicting human behavior (Ajzen, 2012; Kaufmann et al., 2009). The TPB has been used in many ABMs of technology adoption outside the agricultural domain (see Schwarz and Ernst, 2009; Sopha et al., 2013; Jensen et al., 2016; Rai and Robinson, 2015). Furthermore, the TPB makes it possible to model farmers' intentions if actual adoption data is not available, which is a crucial factor for predicting the spread of new technologies via ABMs. In addition, our review of ABMs of adoption of agricultural innovations finds that only a few applications are motivated by social-cognitive theory (e.g. Kaufmann et al., 2009). Groeneveld et al. (2017) also attest a lack of such theories regarding ABMs of land use change. Thus, for ABM modelers, applying this framework can increase the empirical and theoretical foundation, model coherence and comparability of future ABMs.

4.1. Description of the framework

Fig. 4 presents how the model of five stages in the innovation-decision process and the TPB can be combined as a useful tool to model adoption of digital farming technologies. Here, we aim at a balance of integrating empirical farm-level evidence and system interaction. Thus, we made a purposeful selection of empirical variables that are of importance and connect with system elements at the same time. In this way, our conceptual framework presents the holistic picture yet highlights important empirical factors (with red bold squares) that were shown to have considerable impacts by empirical studies. Evidence about impacts of other factors needs to be elucidated in future research. Different theories and categories of determinants are depicted in different colors (see the legend of Fig. 4). We present the factors in the category "psychological factors" (i.e. core concepts in the TPB) and the category "attributes of technology" (from the DOI) in detail because of their theoretical foundations in the respective frameworks, which are directly linked with farmers' adoption decisions. Factors in the other four categories are collectively illustrated for clarity and simplicity. It shall be stressed here that it is not our intention to promote future models aiming to analyze adoption of digital farming technologies to explicitly represent *all* processes and factors depicted in our framework. It is rather meant as a systematization for making conscious specification choices in view of own specific objectives. The conceptual framework is explained below.

(1) In the **knowledge** stage, a farmer becomes aware of a technology's existence and eventually gets interested in it. Knowledge (or awareness) about a new technology comes from "interactions" including learning from other agents and obtaining information from other sources (Rogers, 2003). Interactions themselves influence the observability of digital farming technologies by e.g. farm visits, which likewise impact a farmers' knowledge (Kuehne et al., 2017). The stage of knowledge can usually be modeled through the spreading of information in a social network (see Beretta et al., 2018).

(2) The **persuasion** stage is where a farmer ascertains the potential value of adoption. The TPB postulates that a person's intention is determined by attitude, subjective norm, and perceived behavioral control. **Attitude**, in our case, is a farmer's positive or negative evaluation of adoption. It is influenced by farmer's assumptions about the relative advantage, compatibility of the technology to the existing farm equipment (see Shiau et al., 2018), and data safety of the technology. Relative advantage (especially profitability) depends on the cost and benefit of the technology, farm characteristics and input and output markets (see the grey dotted box) from an economic perspective (Robertson et al., 2012). Compatibility refers to the technical adaptability of the innovation to the existing equipment and practices in the farming system (Robertson et al., 2012). **Subjective norm** is the perceived level of approval or disapproval of adoption by "important others" (Kaufmann et al., 2009). It does describe a receptiveness to normative sanctioning rather than the prescription or prohibition conveyed by a norm (Rasch et al., 2016). It is influenced by policies (connected with "institutions") and social norms in farmers' social networks. Social norms are influenced by institutions and interactions (mainly with respected farmers and consultants) (Pino et al., 2017). **Perceived behavioral control** refers to a farmer's believed ability to implement adoption. It is influenced by a farmer's financial ability, complexity, and trialability of the technology. Farmers' financial ability depends on both incomes (included in operator characteristics) and subsidy/credit accessibility (included in "institutions") (Pino et al., 2017). Perceived complexity depends on operator characteristics, especially their knowledge and capacity, which might change through interactions in social networks.

(3) After the persuasion stage, where intention is formed, a farmer decides to adopt or reject at the **decision** stage. This can be done by setting a threshold of intention for adoption and using either deterministic or probabilistic decision models (Kaufmann et al., 2009; Ng et al., 2011). The latter might be constructed along observed adoption rates in farm populations.

(4) The **implementation** stage is where production activities of a farm are carried out based on the farmer's adoption decision. For example, a farm produces with the objective of maximizing the profit subject to farm endowments (including machinery) and environmental regulations. Farm-level production activities, potentially influenced by the new technology if it is adopted, largely depend on the input market and contribute to the output market. In the long run, changes in markets influence characteristics of farms and lead to structural change (Appel et al., 2016). The link between the input market and "interactions" refers to the fact that technology providers, suppliers and contractors are participating in the input market. Furthermore, production activities impact on the environment and type and severity of the impact depend on the technology used (Weersink and Fulton, 2020). Changes in the environment affect a farm's options of cultivation, for example by changing soil productivity (Aubert et al., 2012; see connection with "farm characteristics"). Environmental pressures may induce policy-makers to adjust regulations (Berger et al., 2007; see connection with "institutions"), and influence the behavior of other agents in the system (Sun and Müller, 2012; see connection with "interactions").

Note that "implementation" stage is optional to model, depending on whether effect of adoption on production, market, or environment should be analyzed or not. Some ABMs stop after observing adoption rate at "decision" stage (e.g. Kaufmann et al., 2009). But including "implementation" stage and next stage ("confirmation") completes the theoretical cycle of adoption.

(5) The **confirmation stage** refers to an evaluation based on whether the criteria initially set up for adoption/rejection has been met. The farmer confirms if the technology will be considered for the next simulation period according to the performance of the technology and the investment cost. This implies that dis-adoption and mal-adoption are allowed. Farmers' evaluations are input for technology providers (included in "interactions") such that they can improve some attributes of the technology (see the connection between the green dotted box and "interactions"). Xu et al. (2020) provide a good example illustrating how the confirmation stage can be modeled.

4.2. Applying the framework

This framework can be applied in studies investigating impacts of policy measures (such as subsidy to procure and regulations of data safety), technology attributes (such as price and compatibility), and interactions in social networks (such as extensions and contractors) on farmers' adoption decision on regional level. As results of such studies will not only improve our scientific understanding of the relevant processes, its application may also inform policy-makers about the potential impacts of policy intervention by scenario development or modeling outcomes. A specific application could be to assess the environmental and economic impacts of adoption and diffusion of mechanical weeding robots and how these are influenced by pesticide policies.

It is worth noting that the implementation of this framework will require a more detailed specification in the context of the specific technology, region, and policy to be analyzed. Such more detailed specifications comprise the quantification and aggregation of farmers' attitude, subjective norm and perceived behavioral control (Schlüter et al., 2017), the identification of the main processes of interaction between farmers and other types of agents, and decisions on how other farmers' decisions (e.g. on production level and intensity) interact with the adoption and diffusion process and its impacts. A specific application benefits from the general setup of the framework but the context provides what matters more and what less.

5. Conclusion

To build an empirically grounded conceptual framework for modeling adoption and diffusion of digital farming technologies, this paper combines knowledge of technology adoption generated from empirical farm-level adoption studies and ABMs simulating systemic diffusion mechanisms.

We first review 32 empirical farm-level studies on the adoption of precision and digital farming technologies. Results show that the majority of farm-level studies focus on farm and operator characteristics, while only a few recent studies highlight the importance of attributes of technology (e.g. compatibility to existing farming equipment, complexity and data safety), institutional and psychological factors. To compare the importance of determinants for adoption, we calculate their partially standardized coefficients. Our analysis shows that among the most frequently investigated factors, farm size has the largest average importance, followed by education, while age does not seem to be a linear predictor for adoption, because of its varying and inconsistent impacts found by various studies. Thus, further investigation is needed to find out whether age influences adoption of digital farming technologies through farmers' other characteristics (e.g. experience, innovativeness, and risk preference) or because of farmers' life stages. Although the observations of psychological factors and attributes of technology are limited, their consistency and high level of importance remind us that they could be useful predictors for farmers' adoption decisions. To obtain more evidence, future adoption studies of digital farming should explore the impacts of psychological factors and attributes of technology on adoption (especially the potential impact of data safety).

Due to the limitation of farm-level studies not capturing linkages between determinants and feedback within the complex adaptive system, we further review 27 ABMs of diffusion of agricultural innovations. We find that current ABMs of agricultural innovations only loosely connect with empirical farm-level findings, despite their usefulness for representing system interaction. They are quite limited with respect to modeling various types of agents, and are largely characterized by profit maximization while rarely modeling farmers' knowledge/capacity, psychological factors, attributes of technology and institutional arrangements. While ABMs are well aligned with the theory in terms of endogenous macro-phenomena postulated by the theory of diffusion of innovation, they are not well-grounded in empirical details yet. This latter weakness might be a characteristic of ABMs of agricultural innovations just recently evolving from the early toy and proof of concept models to more empirically tuned ones. A natural next step in this evolution is to consider the wealth of research found in the empirical farm-level adoption studies.

Based on the loose ends between both literature strands, we present a conceptual framework integrating farm-level evidence and system interaction for modeling adoption and diffusion of digital farming technologies in crop production. The framework is aligned with the theory of diffusion of innovation and with the theory of planned behavior. It uses well researched farm-level adoption determinants from a system perspective and connects important factors based on empirical evidence.

To the best of our best knowledge, this work constitutes the first proposal for a conceptual framework for adoption and diffusion of digital farming technologies in crop production. It improves our current understanding of mechanisms of adoption and diffusion of digital farming in this context. Our framework also serves as a reference for future ABMs capable of integrating empirical evidence and system dynamics holistically. Applying this framework can increase the empirical and theoretical foundation, model coherence and comparability of future ABMs. Furthermore, the framework provides structural hypotheses that can be examined by researchers who aim to understand farmers' decision-making of adoption using farm-level approaches or by those who investigate diffusion mechanisms of digital farming technologies using complex systems approaches.

There are some limitations in this study that could be addressed in future research. First, we reviewed adoption studies of generic precision and digital farming technologies in crop production. This leads to a fairly broad conceptual framework containing factors that might not be relevant for some specific technologies. Focusing on specific technologies (e.g. mechanical weeding robots) will allow to start from this general framework but require to specify the contextual relevance of the determinants.

Second, our conceptual framework is only based on a limited number of studies available at this time. This causes uncertainty regarding the importance of mostly unexplored factors such as institutions and social networks to farmers' adoption decision. We suggest to tackle these context-specific issues with the future development of diagnostic procedures (Cox, 2011) going hand in hand with our framework to deliver clear-cut interpretations for institutions and network types.

Last but not least, the proposed framework is largely based on the existing theories (i.e. DOI, TAM, and the TPB) applied in the reviewed studies. These theories have certain limitations. Lyytinen and Damsgaard (2001) question the completeness of the list of technology attributes defined by the DOI and whether all innovations should be characterized with the same set of attributes. TAM is criticized because it ignores the social influence on adoption (Beldad and Hegner, 2018). Frequently reported limitations of the TPB include its predictive validity, rationality assumption, and omitting the effect of habits and emotions among others (Ajzen, 2011). Therefore, these theories might need to be adjusted when dealing with different technologies in different social and political contexts.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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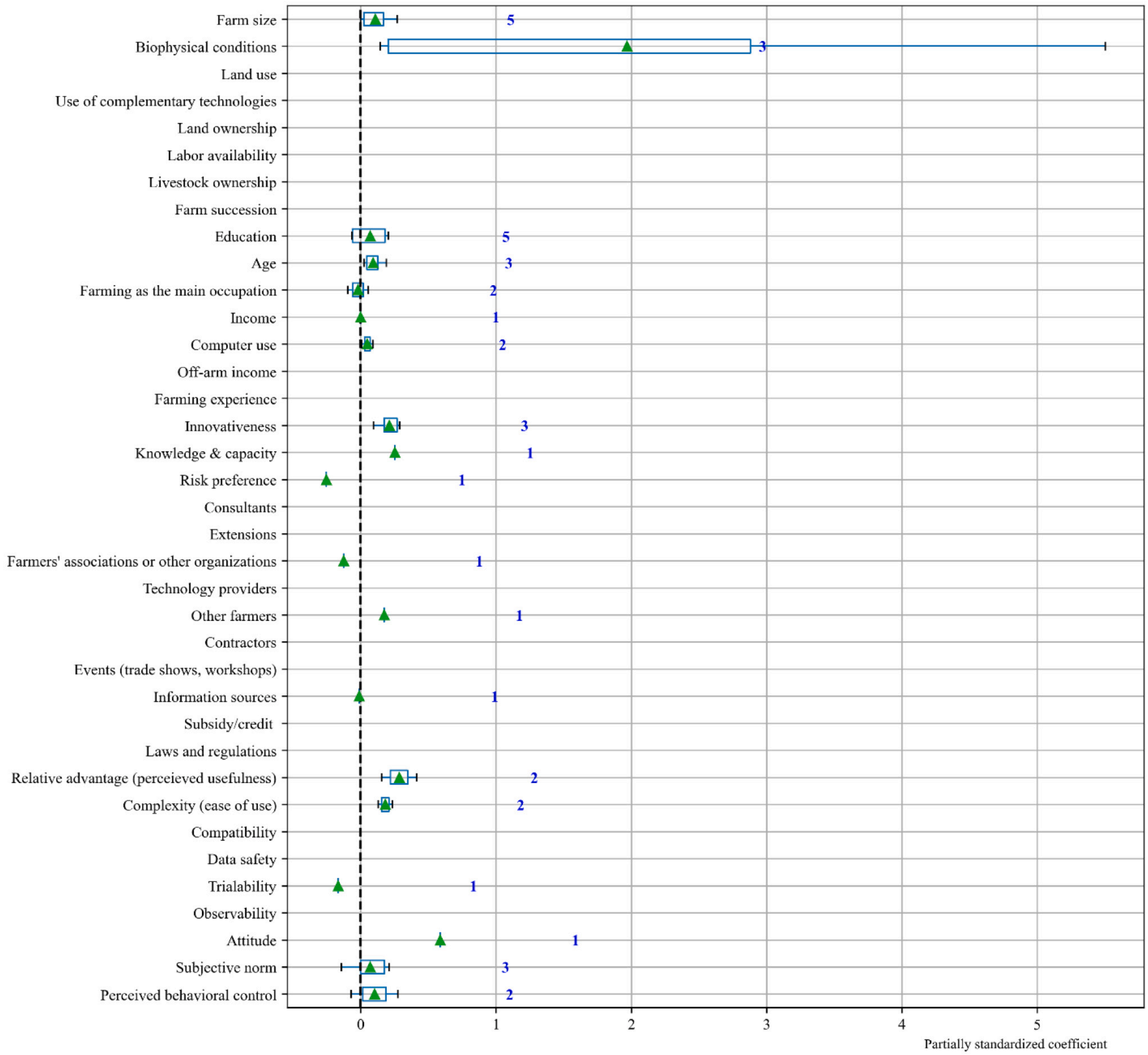
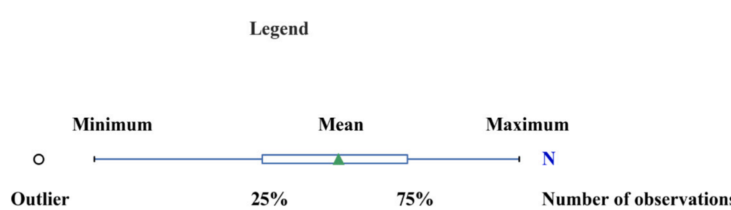
Appendix 1. Selected empirical farm-level studies of technology adoption

No.	Study	Technology type	Research Region	Method
1	Adrian et al. (2005)	precision farming	USA	structural equation model
2	Asare and Segarra (2018)	precision farming	USA	probit model
3	Aubert et al. (2012)	precision farming	Canada	partial least squares
4	Barnes et al. (2019)	precision farming	Belgium, Germany, Greece, the Netherlands and the UK	logit model
5	Boyer et al. (2016)	precision farming	USA	probit model
6	Caffaro and Cavallo (2019)	smart farming	Italy	structural equation model
7	D'Antoni et al. (2012)	precision farming	USA	logit model
8	Drewry et al. (2019)	digital farming	USA	descriptive analysis
9	Gallardo et al. (2019)	precision farming	USA	probit model
10	Isgin et al. (2008)	precision farming	USA	logit and poisson models
11	Kutter et al. (2011)	precision farming	Germany	descriptive analysis
12	Lambert et al. (2014)	precision farming	USA	logit model
13	Lambert et al. (2015)	precision farming	USA	logit model
14	Larson et al. (2008)	precision farming	USA	logit model
15	Lencsés et al. (2014)	precision farming	Hungary	ANOVA test
16	Lynne et al. (1995)	Micro-drip irrigation	USA	tobit model
17	Michels et al. (2020)	smart phone in farming	Germany	logit model
18	Mitchell et al. (2018)	precision farming	Canada	descriptive analysis
19	Paustian and Theuvsen (2017)	precision farming	Germany	logit model
20	Pedersen et al. (2004)	precision farming	Denmark	descriptive analysis
21	Pino et al. (2017)	water-saving measures (micro-drip, sprinkling irrigation, plastic sheeting)	Italy	structural equation model
22	Pivoto et al. (2019)	smart farming	Brazil	logit and poisson models
23	Pokhrel et al. (2018)	precision irrigation	USA	poisson model
24	Reichardt and Jürgens (2009)	precision farming	Germany	descriptive analysis
25	Robertson et al. (2012)	precision farming	Australia	logit model
26	Salimi et al. (2020)	automation	Iran	structural equation model
27	Schimmelpfennig and Ebel (2016)	precision farming	USA	probit model
28	Takácsné György et al. (2018)	precision farming	Hungary	descriptive analysis
29	Tamirat et al. (2017)	precision farming	Denmark and Germany	logit model
30	Vecchio et al. (2020)	precision farming	Italy	logit model
31	Walton et al. (2008)	precision farming	USA	probit model
32	Zheng et al. (2018)	unmanned aerial vehicles	China	probit model

Appendix 2. Partially standardized coefficients of factors from models with binary outcome





Source: own results.

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