ADOPTION AND DIFFUSION OF DIGITAL FARMING TECHNOLOGIES - INTEGRATING FARM-LEVEL EVIDENCE AND SYSTEM-LEVEL INTERACTION

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Summary

Adoption and diffusion of digital farming technologies are expected to transform current agriculture towards a more sustainable system. Yet, to enable a targeted transformation we need to understand the mechanisms of adoption and diffusion in a holistic manner. Our current understanding comes from separate empirical farm-level studies on individual adoption and agent-based models (ABMs) simulating systemic diffusion mechanisms. Our objective is to bring both strands of literature together. We review 32 empirical farm-level studies on the adoption of precision and digital farming technologies and 27 ABMs on the diffusion of agricultural innovations. Results show that farm-level studies focus on farm and operator characteristics, but pay less attention to attributes of technology, interaction, institutional and psychological factors. ABMs, despite their usefulness for representing interaction on higher scales, 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 system-level interaction of technology diffusion. It may serve as a reference for future ABMs modeling adoption and diffusion of digital farming technologies at larger scales.

Keywords

technology adoption, innovation diffusion, digital farming, agent-based modeling, farm level, systematic review

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 devices for decision support, over in-field sensors and remote sensing technologies for better decision making, and to drones and robots for the automation of processes (see OECD (2019) for detailed categories of digital farming technologies).

To enable the transformation towards more sustainable agricultural systems, we need to understand mechanisms of adoption and diffusion of digital farming technologies on both farm and system level. Adoption behavior not only depends on farm and operator characteristics but is also influenced by structural, political and economic conditions of the agricultural system. Some of these conditions emerge and evolve from the joint, but heterogeneous, and interactive behavior of farmers. It is this interaction in combination with, and depending on, individual farm characteristics that will ultimately determine technology diffusion and its impact on the sustainability of the agricultural system. Therefore, it is necessary to understand not only individual adoption but also system feedback in the process of adoption and diffusion.

So far our understanding of the mechanisms of technology adoption and diffusion comes from separate empirical farm-level studies on individual adoption and agent-based models (ABMs) simulating systemic diffusion mechanisms. Although 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), they are still rare. This lack of information requires us to also refer to the lessons of precursor technologies, i.e. precision agriculture technologies (PATs). For both PATs and digital farming technologies, empirical farm-level studies investigate determinants of adoption using different methods and/or applying different theories (see section 2 for a review of these). However, farm-level adoption studies do not consider any system-level feedback. 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. System dynamics at larger scales are usually well captured by ABMs, as they are meant for considering endogenous feedback between different interacting entities (agents) and their higher-level phenomena. They 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.

Acknowledging both, the relevance and current separation of these two strands of literature, this paper aims to integrate individual-level determinants and system-level feedback for building real-world models of adoption and diffusion of digital farming technologies. Establishing this connection might allow us to understand how farmers' (adoption) behavior influences the larger scale and how changed system conditions in turn affect what is happening at the farms. This dynamic and spatially differentiated process ultimately determines technology diffusion and its understanding could help us to identify effective pathways for more sustainable agricultural systems. Therefore, we develop a conceptual framework integrating farm-level evidence and system-level attributes of adoption and diffusion of digital farming technologies to address the limitations of both farm-level studies and ABMs (see section 4). Such integration will not only improve our scientific understanding of the relevant processes, it also has the potential to ultimately inform policy-makers trying to foster implementation of suitable digital technologies through extension services and service providers. The last section (section 5) concludes the paper.

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 resulted in 1,266 identified studies.

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)	6,694
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	1,266

Source: own results

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

Only studies that focus on determinants or influencing factors of adoption of technologies in crop production are selected resulting in 32 studies that were reviewed (see Appendix 1). Nearly half of them (14) was conducted in the USA; 12 studies in European countries; and the rest in Canada (2), Australia (1), Brazil (1), China (1), 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. Figure 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, as shown in x-axis of Figure 1) instead of the number of studies. Factors are grouped into 6 categories: farm characteristics, operator characteristics, interactions, institutions, attributes of technology and psychological factors. Figure 2 summarizes partially standardized coefficients of factors representing their importance (i.e. size effect) in farmers' adoption decisions.

2.2 Significance of factors

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 studies. 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** contributes to the adoption of other PATs. 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 (Abdulai et al., 2011). However, none of the 8 studies 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, unskilled labor availability and cost could be the main drivers of robotic farming technologies.

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** seems to be of negative impact. The complexity of modern 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 and autonomous 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, 2017; 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).

Interactions

Interactions are vital for the diffusion of a new technology. 1) Having **consultants** is often found 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. Asare and Segarra (2017) report a negative impact of having contact with university extensions on adoption of soil sampling technology, while in Larson et al. (2008) farmers who believed that information from extensions are helpful tended to be adopters of remote sensing technology. The interview of Kutter et al. (2011) consider 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 technology providers are believed to promote adoption (Drewry et al. 2019; Barnes et al., 2019). 5) **Other farmers** can influence farmers' decisions through information exchange. However, the 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 and 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.

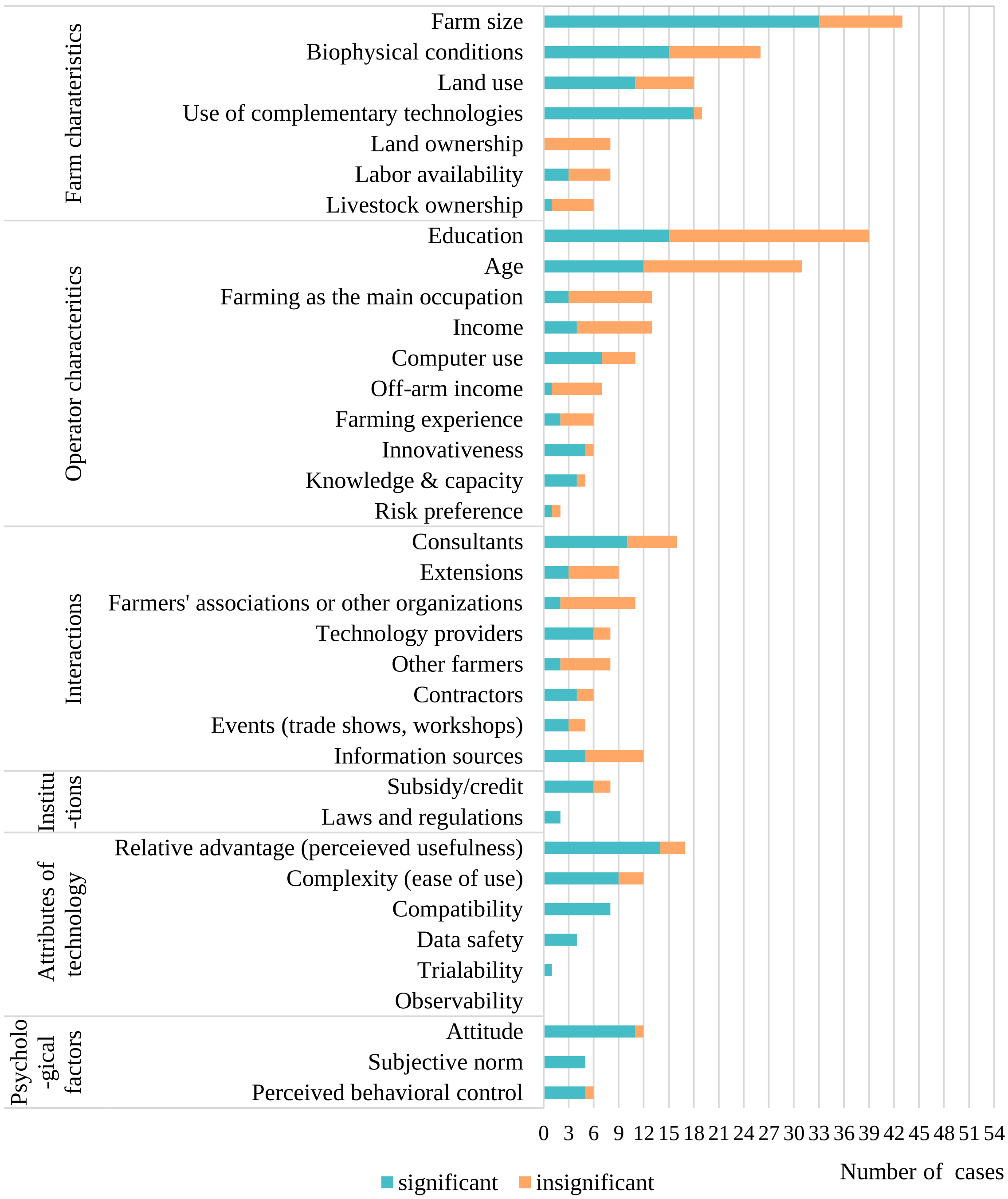

Figure 1: Influencing factors on farmers' technology adoption decision synthesized from 54 cases

Source: own results

Institutions

Institutional factors are norms and regulations in society. 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:** Increasing environmental requirements (e.g. stringent laws on pesticide and nitrogen application) are one of the forces for adoption of PATs (Barnes et al., 2019; Kutter et al., 2011). In the context of digital farming, regulations on data ownership are needed to avoid misuse of farms' data (Barnes, et al., 2019).

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. 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, high yield or profitability 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 (Pivito et al., 2019). 3) **Compatibility** of new farming technologies to existing machinery, poor telecommunication infrastructure and data interoperability are constraints of precision and robotic farming technologies, mentioned by 7 out of 8 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. Concern about the misuse of digital data by commercial service providers makes farmers more cautious (Kutter et al., 2011).

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. 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 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 in our case, 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 (Figure 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.

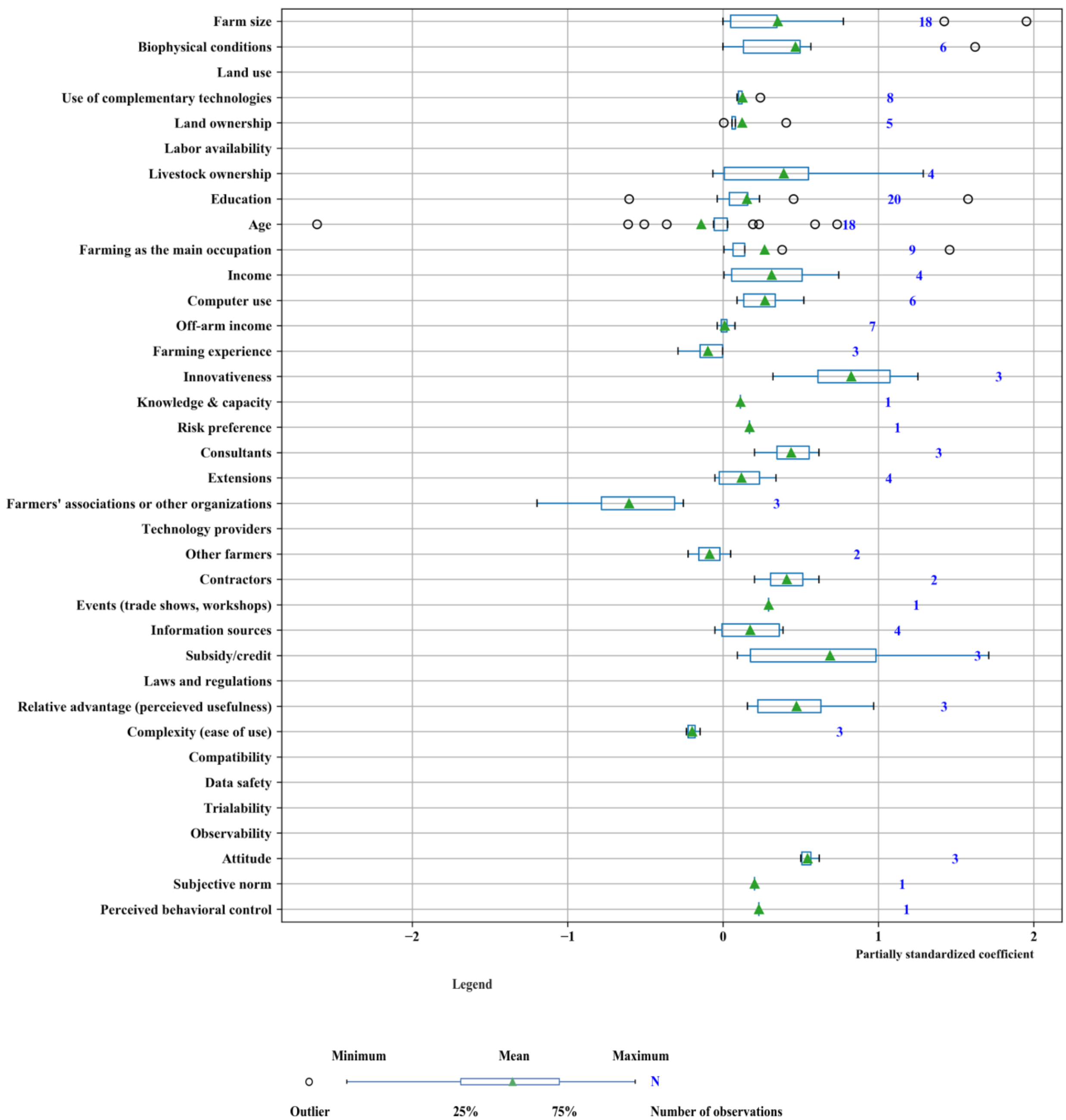

Figure 2: Partially standardized coefficients of factors from models with binary outcome

Source: own results

[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.

The boxplot in Figure 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.

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 the highest mean value (0.35), followed by 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 one exception. 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 seems 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) seems to have a smaller impact on adoption than total income (4 observations, mean = 0.313). 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 in the figures for the inspection by readers.

2.4 Limitations of farm-level studies and the need for ABMs

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. 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.

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. An important contribution in this regard is ABMs. They are methodologically geared at explicitly considering endogenous feedback between individual decision-making units and macro-level phenomena. They enable researchers to create, analyze and experiment with models composed of agents that interact with each other and with the environment (Gilbert, 2007). These interactions give rise to dynamics at higher scales that agents can perceive and adjust to, which potentially influences the overall dynamics on system level once again, thus forming new macro-level phenomena like innovation diffusion (Galán et al., 2009). For example, ABMs can easily model one of the central elements in the theory of DOI, peer interaction, in the process of technology diffusion, while it is rarely considered by farm-level studies as shown in Figure 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. (Kremmydas et al., 2018). In section 3, we will explore factors that are considered in current ABMs of agricultural innovations.

3 System-level studies: 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. Note that we only included innovation adoption of farmers rather than e.g. of consumers adopting new cellphones because farmers' decision-making is not only bounded by budgets and personal preferences but also by their production activities. Due to the limited amount of ABM studies in this field, we did not limit our scope to adoption of technologies but also include other innovations (e.g. new practices, crops, etc.) to get a better picture of the methodology and limitations of current ABMs.

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*)	5,129

2	TS = ("agent-based" OR "agent based" OR "abm" OR "multi-agent" OR "multi agent") AND TS = (agricultur* OR farm* OR water OR crop)	1,293
	Combine 1 and 2	265

Source: own results

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

After further screening, we selected 27 ABM studies that explicitly modeled adoption or diffusion of agricultural innovations including conservation practices and programs (8 studies, e.g. Sun and Müller, 2013), 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 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. Figure 3 shows factors that directly affect the adoption decision process (i.e. triggers) and factors considered elsewhere (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 Figure 3, studies are ordered according to the similarity of their adoption behavioral 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 (like Berger, 2001; Schreinemachers et al., 2007 and 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 (e.g. Cai and Xiong et al., 2017; Huang et al., 2016) 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. Studies like Kaufmann et al. (2009) and Xu et al. (2018 and 2020) are cognitive models where farmers’ psychological factors like attitude and subjective norms are the only triggers, while farm characteristics are to a great extent ignored. Typology models of Daloğlu et al. (2014a)[2] and Sengupta et al. (2005) assign a probability of adoption according to a few features of the agent, thus allow multiple triggers from different categories for adoption. But determining the probability of adoption at the beginning of the simulation forces the agents to “give up” the ability to communicate. 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 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 (2013) 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 Figure 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 2015; Sorda et al., 2013; Cai and Xiong, 2017; and Manson et al., 2016). **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 Kauffmann et al., 2009; Sun and Müller, 2013; Schreinemachers et al., 2007 and 2009; Holtz and Pahl-Wostl, 2012). Likewise, considerations of substantial investments into complex technologies are bound to the current stage of farmers’ life, 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 (Figure 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 and norms that govern individuals’ behavior but only a few studies have considered them (e.g. Holtz and Pahl-Wostl, 2012). 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 (see Barnes et al. 2019).

[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.

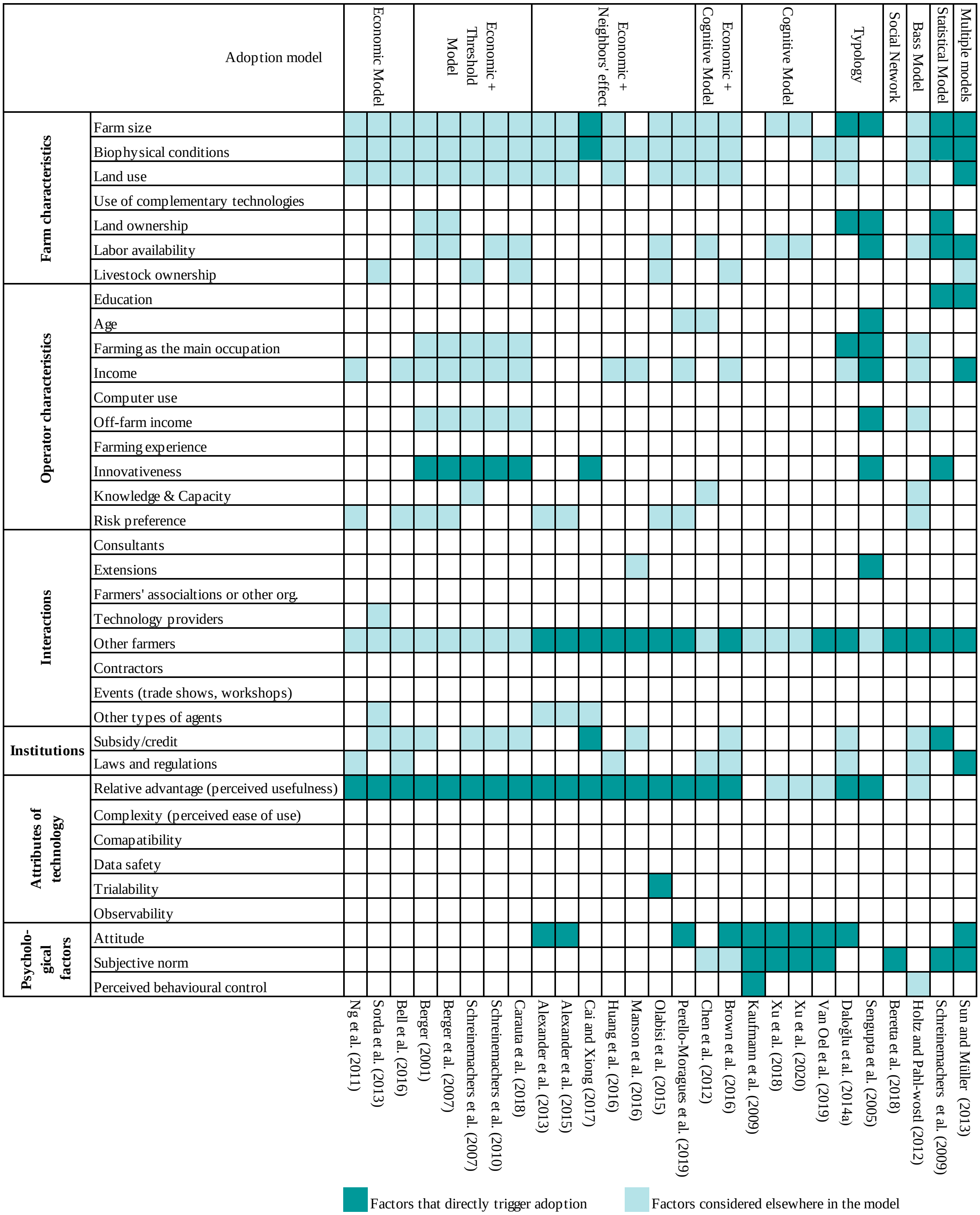

Figure 3: Factors influencing adoption and adoption models in ABMs of agricultural innovations

Source: own results

4 A conceptual framework for empirically grounded ABM

Having identified the loose ends of both strands of literature, we aim to conceptualize potential links between farm-level determinants and system-level attributes for real-world models of adoption and diffusion of digital farming technologies. 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 in research 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.

Figure 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 to 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 Figure 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 ABMs aiming to analyze (digital) technology adoption 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. Applying this framework can potentially increase model coherence and comparability for the ABM community. 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 is likewise impacting 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 and compatibility of the technology to the existing farm equipment (see Shiau et al., 2018). 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 mainly respected farmers and consultants (included in "interactions") (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, trialability of the technology, and data safety. 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 be a function of a farmer's age and education.

(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 farm activities are carried out based on the farmer's decision. This can be realized by various algorithms (e.g. mathematical programming, artificial neural network, Bayesian belief network, etc.). Farm-level production activities, potentially influenced by the newly adopted technology, 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, 2013; see connection with "interactions").

(5) Confirmation 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. 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.

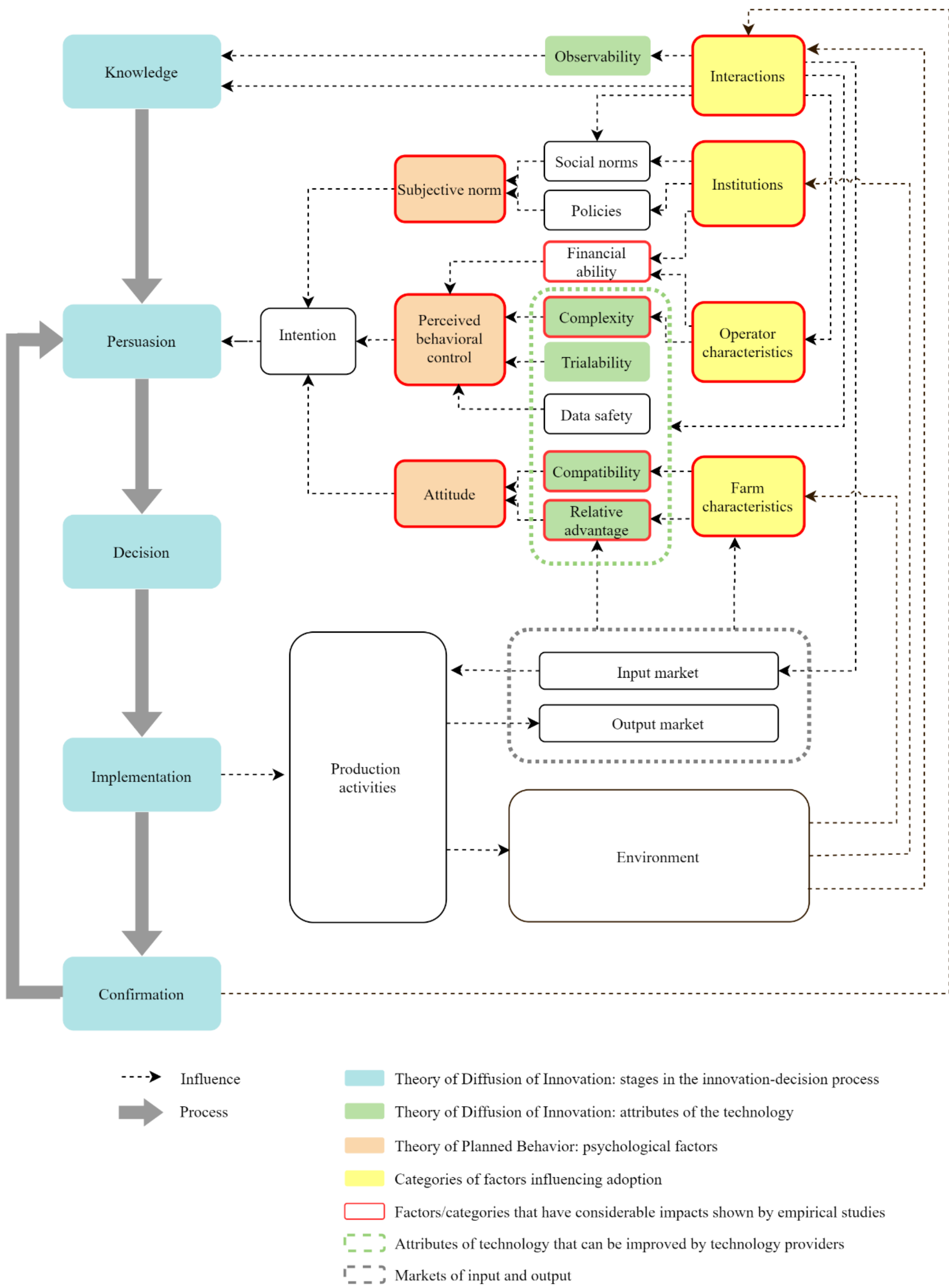

Figure 4: Conceptual framework for empirically grounded ABMs of adoption and diffusion of digital farming technologies

Source: own illustration

5 Conclusion

To improve our understanding of mechanisms of adoption and diffusion of digital farming technologies, this paper combines knowledge of technology adoption generated on farm-level and system-level simulation studies.

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 consistent and high level of importance reminds us that they might have the potential to 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 system-level studies - agent-based models 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 interactions on higher scales. 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 as well-grounded in empirical detail, 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-level interaction for future ABMs of adoption and diffusion of digital farming technologies. 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 existing 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. It improves our current understanding of mechanisms of adoption and diffusion of digital farming. Our framework 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.

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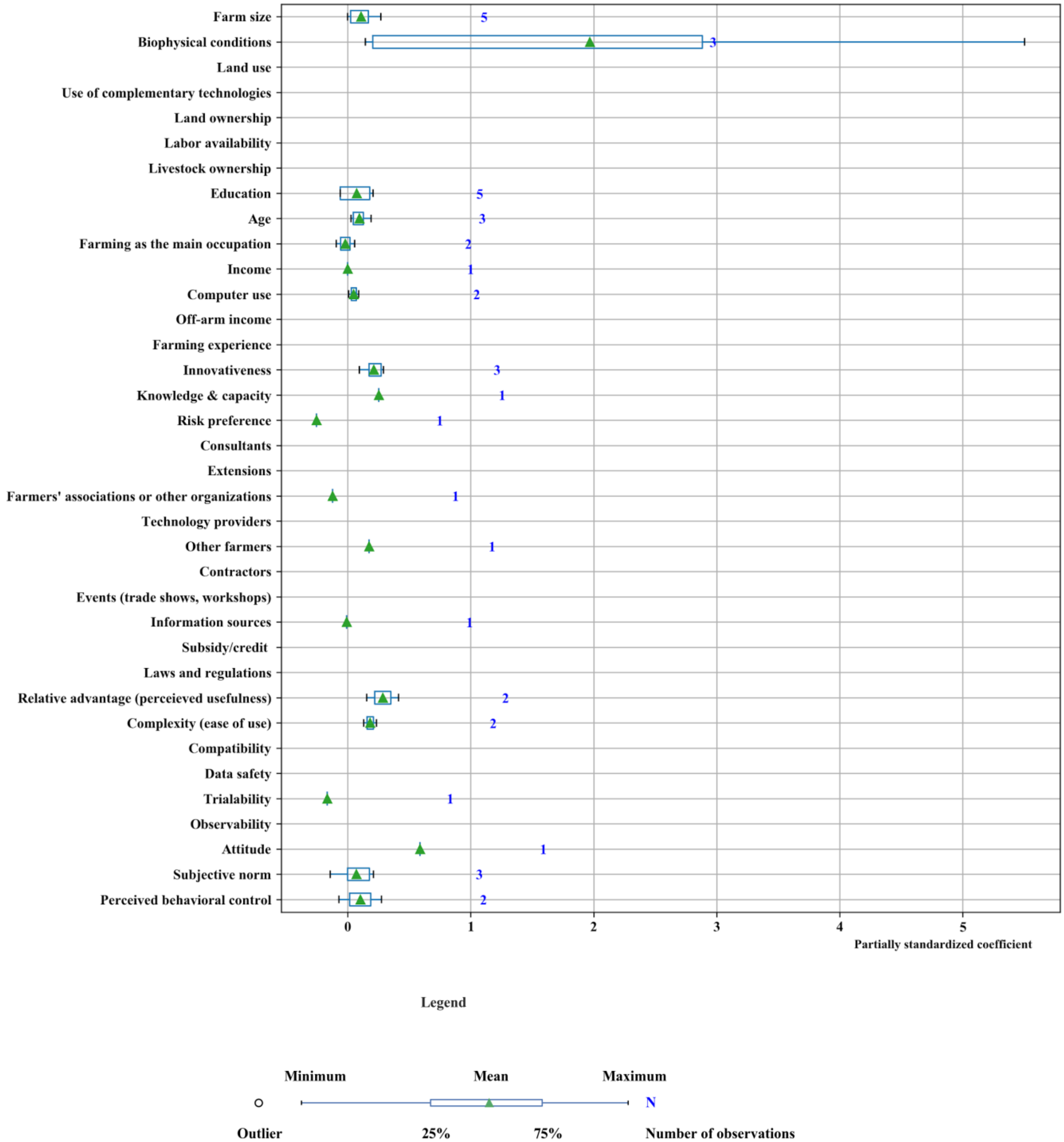
Appendix 1: Selected empirical farm-level studies of technology adoption

No.	Study	Technology type	Research Region	Method
1	Adrian et al. (2005)	precision farming	USA	structural equation model
2	Asare and Segarra (2017)	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