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The leading role of perception: the FACOPA model to comprehend innovation adoption

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Abstract

In this work, we explore the link between the perception of complexity and the possibility of adopting precision agricultural tools (PATs). Many studies have analysed the role of perception, mostly considering it a determinant of adoption on the same level as other contextual factors. In contrast, this study contributes by assuming that farmers' perceived complexity is the main factor influencing their propensity to innovate and should be analysed on a different level. Starting from this assumption, a new theoretical model is proposed with the aim of studying the "factors–perception of complexity–adoption" (FACOPA) process. To test the validity of our hypothesis, a survey is conducted based on a purposive sample of 285 farmers. First, a linear regression model permits us to identify determinants of the perception of complexity. Then, a multinomial logistic model is used to determine which aspects of perceived complexity may affect the choice to adopt precision farming tools made by three different types of agricultural entrepreneurs: adopters, non-adopters, and planners. First, the linear regression results show that socio-structural variables have a logical relationship with perceived complexity, with age, farm size, the intensity of information and the intensity of work being significant. Then, the multinomial logistic model highlights that non-adopters perceive almost all aspects of complexity as barriers to adoption. Planners show a lower perception of complexity than non-adopters, with complexity being determined by financial and network aspects. The results provide interesting suggestions for policy-makers. Indeed, the FACOPA model offers insights into an intervention framework in which policy measures can be diversified to disseminate PATs based on farmer categories. Non-adopters require a broader set of policy instruments, while planners should be encouraged to become adopters through financial support and the activation of innovation networks.

Keywords: Perception, Innovation, Precision agriculture, Adoption process, Complexity

Introduction

Precision farming is a whole-farm management approach based on a set of information technologies, and its adoption makes it possible to both improve farms' profitability and optimize yields and their quality while reducing environmental impacts (Zarco-Tejada et al. 2014; Barnes et al. 2019). The adoption of precision agriculture (PA) enables farmers to reduce negative externalities such as biodiversity loss, the over-exploitation of

resources and CO_2 emissions (Pretty 2001; Ogle et al. 2014). For this reason, policies at the European level are promoting PA adoption: in the recent communication "The future of food and farming" (EC 2017), PA could have a dedicated area within rural development policies. Nonetheless, technology adoption raises wider questions of "complexity" that should be analysed in depth.

Most studies speak of "complexity" with the aim of describing the multidimensional scenario of the factors influencing innovation adoption. The socio-structural characteristics of farms, farmers' perception, and factors linked to the institutional context contribute to depicting this complex framework (Pierpaoli et al. 2013). This paper argues that this complexity needs to be reviewed from the point of view of the potential adopter, defining the concept of "perceived complexity". From this perspective, this paper does not analyse the direct effect of factors on the propensity to adopt; rather, it aims to provide an original contribution by proposing the "factors–perception of complexity–adoption" (FACOPA) model. More precisely, this paper tries to provide a new approach under the hypothesis that perceived complexity is the main driver affecting the propensity to innovate. By emphasizing perceived complexity and with the purpose of measuring it, the paper aims to contribute to the abundant literature on technology adoption with special reference to the uptake of precision farming tools. The specific purpose of our analysis is not to focus on one specific innovation related to PA but to evaluate farmers' behaviour of either adopting PA or not.

The paper is organized as follows: "Theoretical background: problematizing complexity in innovation adoption" section provides a conceptualization of the complex scenario of adoption from the perspective of farmers. Section 3 presents the materials and methods, while the results are presented in "Results" section and discussed in "Discussion" section, jointly with conclusions and policy implications.

Theoretical background: problematizing complexity in innovation adoption

Farmers do not adopt innovations simultaneously due to different propensities to innovate (Diederen et al. 2003). This means that every process of innovation is characterized by complexity and requires time. As pointed out by actor-network theories, innovation involves four stages (Faure et al. 2018): problematization, engagement, enrolment and the mobilization of actors. Moreover, innovation is a complex and unpredictable process (Leeuwis and van der Ban 2004) that involves not only technical but also social aspects, as posited by the school of sociotechnical transition (Geels and Schot 2007; Darnhofer 2015). As a consequence, complexity is characterized by numerous determinants influencing farmers' decision to adopt (Pierpaoli et al. 2013; Aubert et al. 2012), such as the socioeconomic characteristics of farms, financial constraints, and the social and institutional contexts (Reimer et al. 2012; Barnes et al. 2019; Say et al. 2018; Struik et al. 2014). With the purpose of proposing a socio-structural factors–perception of complexity–adoption model, this section is organized as follows:

- "Factors affecting the adoption level of PA technologies" section presents the most widespread approach proposed in the literature to date, which is the "factors–adoption model", based on which scholars mainly study the direct influence of socio-

structural and institutional variables and farmers' perceptions of technologies on the decision to adopt.

- "The mediating role of perceived complexity" section presents the FACOPA model proposed by the present study, in which perception plays a key role in the adoption process. In this model, the concept of perceived complexity, in which the influence of the institutional context is embedded, is shaped by socio-structural variables.

Factors affecting the adoption level of PA technologies

The literature has recognized the relevance of key variables acting as barriers to/drivers of innovation adoption. More precisely, socio-demographic and structural variables, such as the personal traits of farmers, the style of farming, and economic factors, play a fundamental role in affecting the innovation adoption decision (Say et al. 2018).

Regarding sociodemographic variables, young farmers are more willing to bear risk and to experiment with new paths in farm management (D'Antoni et al. 2012; Paxton et al. 2011; Ajewole 2010). Moreover, young farmers are more knowledgeable about innovations because of their longer time horizon and their "attitude of confidence" with technologies (Adrian et al. 2005; Far and Rezaei-Moghaddam 2017). Only a few studies show older farmers as adopters since they generally rely on a higher level of experience (Walton et al. 2010; Khanna 2001; Isgin et al. 2008). In addition, farmers' skills matter: beyond the wealth of experience, studies describe adoption as a learning process that requires capabilities to interpret information (Kitchen et al. 2002; van der Weerdt and de Boer 2016). Additionally, adoption is positively related to a high level of education (McBride and Daberbow 2003a; Long et al. 2016; Läpple et al. 2015). Regarding structural variables, farm size plays a relevant role. Large and capital-intensive farms show a greater capacity to bear costs and risks (Miller et al. 2017; Läpple et al. 2015; Lambert et al. 2015). In many cases, a farm's structure is strictly linked to credit access. Farmers with higher financial resources are generally more oriented towards adoption (Griffin et al. 2004; Robertson et al. 2012). Initial investment in technologies and the excessively long payback period have an impact on users, who must accept a temporal asymmetry between the costs and benefits derived from adoption (del Río Gonzalez 2005; Long et al. 2016). PA implementation requires high costs, such as transaction, switching, training and information costs, which might be onerous, especially for small farms (Feder et al. 1985; McBride and Daberkow 2003b; McCarthy et al. 2011). Of course, the size of these costs depends on the profile of the technology to be adopted; this raises the question of the "best fitting" technological solution related to farms' crop orientation. In their work, Paustian and Theuvsen (2016) report that owner-occupied farms have greater financial resources to invest in PATs rather than renters. High values of labour intensity may be connected with high levels of PA adoption (Vecchio et al. 2020a), where new technologies allow a reduction in manual labour (De Baerdemaeker 2013).

Additionally, behavioural traits, such as farmers' perceptions, could influence adoption (Aubert et al. 2012). Farmers are more inclined to adopt if they perceive an innovation as being better than the current systems in terms of benefits and time savings ("relative advantage") or if the innovation exhibits "ease of use" or is integrated into daily routines (Rogers 2003; Moore and Benbasat 1991; Davis 1989). If the innovation is perceived as

being difficult to use or to understand ("technological complexity"), adoption tends to be lower (Venkatesh and Davis 1996; Sassenrath et al. 2008). This perception of complexity decreases if a farmer has the possibility of trying out the new technology in an experimental setting. The farmer could evaluate its advantages or drawbacks without purchasing it ("trialability"), have proof of the visibility of the results ("observability") and evaluate the "compatibility" with his or her current operations and equipment (Pannell et al. 2006; Aubert et al. 2012; Anselmi et al. 2014). Several empirical cases show that farmers have some difficulties accepting changes in farm organization and processes (Faber and Hoppe 2013; Bessant et al. 2014; Long et al. 2016). *"Organizational inertia"* (Faber and Hoppe 2013; Hoffman and Henn 2008) describes farmers who decide to refuse innovation and return to traditional practices, even when the benefits have been enjoyed (Bewsell and Kaine 2005; Cullen et al. 2013; Sneddon et al. 2011; Wheeler 2008). This inertia often arises in contexts of consolidated cultural habits and established organizational practices (Ceschin 2013). Therefore, the decision to adopt PA can be positively or negatively influenced by social interactions (Edwards-Jones 2006; Kutter et al. 2011; Pathak et al. 2019). A fertile informal institutional context and relational assets (Storper 2001) exert a strong influence on potential adopters. Moreover, in the same group of potential adopters, some *imitative phenomena* could occur (Sneddon et al. 2011; Edward-jones 2006; Kutter et al. 2011; Lima et al. 2018). The decision to either adopt or not could derive from farm staff ("voluntariness of use"). It could come from a need to perform and improve work practices or because PATs are associated with more prestigious products and/or farmers with a higher profile ("image") (Moore and Benbasat 1991; Aubert et al. 2012). Additionally, the institutional context in terms of the environment, politics and socio-cultural dynamics plays an important role in influencing adoption (Edward-Jones 2006; Robertson et al. 2012; Long et al. 2016). Farmers are likely to adopt if external *stimuli (*such as institutions and the advisory system) are supportive of the technology (Fountas et al. 2005; Edward-Jones 2006). In fact, a lack of approval from advisors and a lack of communication between both the supply and demand sides have been found to be barriers to adoption (Long et al. 2016).

### The mediating role of perceived complexity

The previous theoretical background provides an idea of how "complexity" has been explored by measuring the direct effects of socio-structural variables, perception, and the institutional context on adoption. Although the literature has contributed to identifying key aspects of adoption, there is less consensus among scholars on which factors could primarily affect the decision-making process. In fact, most of the literature examines adoption by analysing the influences of both personal and contextual factors by placing them on the same logical level in the adoption framework. Therefore, this paper tries to fill a gap in the literature by arguing that perception plays a primary role in the adoption process and that the influence of the variables mentioned above should be studied on different logical levels.

Some authors have pointed out that the decision of whether to adopt PA can be better explained through the analysis of farmer perceptions (Vecchio et al. 2020b; Ghadim and Pannel 1999; Adesina and Zinnah 1993; Ntshangase et al. 2018). In the term "perceived complexity", scholars have encapsulated some of the most widespread "beliefs" in the

literature when farmers are faced with the choice of adoption (Vecchio et al. 2020b; Tey and Brindal 2012). Nonetheless, if, on the one hand, complexity is a commonly accepted barrier to the uptake of PA, on the other hand, it is necessary to examine how farmers mediate with these factors and why they perceive some barriers more intensively (e.g., financial) than others (e.g., management). In his study on conservative agriculture, Lugandu (2013) proposed a theoretical model in which adoption depends on the perception of the new technology, which in turn is influenced by farmers' characteristics, style of farming and exposure to information. Schirmer and Bull (2014) built a two-step model with the purpose of investigating (1) how the perceived attributes of afforestation influence adoption and (2) how social acceptability, knowledge, experience and socio-demographic characteristics influence landowners' perceptions. The results showed that the individual develops either a positive or a negative perception of afforestation, depending on personal characteristics and the social acceptability of the practice. In the second phase of empirical analysis, some components of the perception explain more than others the willingness to adopt.

This concept has been recently explored in psychological research, which states that background variables (socio-structural and institutional context) shape individuals' perceptions, thoughts and feelings in an endogenous way (Reimer et al. 2012; Markus and Kitayama 2010; Hoff and Stiglitz 2016). Likewise, the same institutional contest is of overriding importance in analysing the variables intervening in innovation adoption. More precisely, as posited by Welter (2011), the institutional context takes into account social attitudes and norms or, according to original institutional economics, the culture shaping the individual's behaviour (Markus and Kitayama 2010). The "cultural turn" in social theory has raised interest in how culture and context shape knowledge and behaviour (Storper 2001): "Culture is a synthesis—or at least an aggregation—of institutions (…) whose function is to set a pattern of behaviour" (Hamilton 1932, p. 3). As a consequence, institutions act as 'hidden persuaders' (Hodgson 2003) and may engender mechanisms of dependency through the consolidation (or institutionalization) of habits and conventions moulding frameworks of action. For this reason, scholars in psychology talk about "encultured" decision-makers, whose perceptions are affected by socio-structural and institutional factors (Fiske et al. 1998; Markus and Kitayama 2010). Against this backdrop, farms' innovation adoption has been modelled as an inherently social process, showing that individuals perceive innovation in different ways (Reimer et al. 2012).

Our hypothesis is that perception could have a primary role compared to other variables. We posit that these variables do not directly influence adoption. Socio-structural and institutional variables contribute at different levels to the formation of individuals' perceptions, which, according to our hypothesis, are a direct determinant of adoption. Furthermore, a new approach overcoming the limitations of Vecchio et al.'s (2020a, b) work hypothesizes that the effects of "culture" are embedded in the concept of perceived complexity, for which a synthetic indicator has been constructed. This indicator comprehends the most relevant "farmer beliefs", indicating the influence of the multidimensional context in which innovation occurs. As a consequence, this paper provides a unique contribution to the literature by investigating the relationship between "socio-structural factors", "perceptions of complexity" and "PA adoption" (Fig. 1), as summarized in the FACOPA model.

Fig. 1 Relationship between the investigated dimensions: The FACOPA model
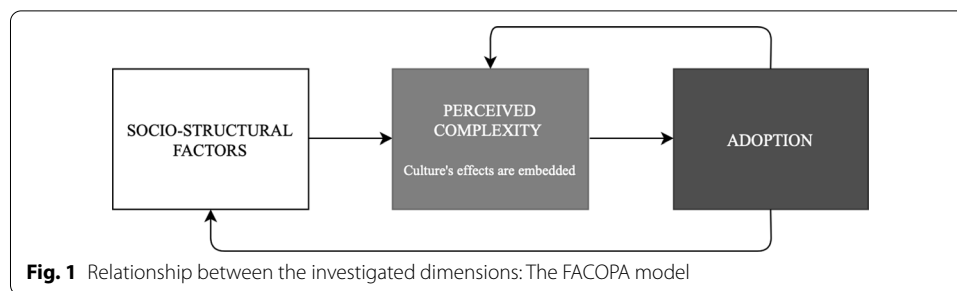
Socio-structural factors contribute to the formation of the perception of complexity, which in turn is decisive for the choice to either adopt or not new technologies. At the same time, adoption, on the one hand, reduces the perception of complexity itself and, on the other hand, influences the socio-structural factors and, in other words, the farm profile. Therefore, we posit that the relation is neither linear nor univocal in that it assumes a multidirectional movement.

Perceived complexity is a result of a composite set of beliefs integrating aspects of the multiple dimensions characterizing the agricultural innovation system and on which the influence of socio-structural variables is exerted. This has evident implications for of empirical measurement.

Materials and methods

To explore the influence of perceived complexity on PAT adoption, a survey was carried out among Italian farmers who participated in national fairs. The surveys were conducted in a face-to-face manner, and the respondents self-completed a paper questionnaire with the support of a researcher. The aim of the analysis is to measure the probability of PA adoption as dependent on perceived complexity, which is established as a composite variable. Therefore, a purposive sample technique was used. A questionnaire was submitted to a sample of 300 farmers. This sampling technique aims to subjectively select interviewees with the purpose of gathering detailed information on the object of study (Kelley et al. 2003).

To obtain a purposive sample, an initial question was asked: "Have you ever heard of precision agriculture?" If the answer was negative, the respondents were excluded from the survey. This choice was due to the desire to have a sample that was at least "aware" of the subject of the survey. For the purpose of exploratory work, purposive sampling is commonly used to collect empirical data (Etikan et al. 2016). The percentage of correctly completed questionnaires was 85.7%. Then, 285 questionnaires were considered valid for our study. The survey was divided into two parts: in the first part, the socio-structural variables were investigated, while in the second part, the variables to extract the perceived complexity of the farmer were designed.

The socio-structural variables are as follows:

- *Age* the age of the holder;
- *Education* the level of education of the holder;
- *Farm size* the utilized agricultural area (UAA) in hectares;

- *Intensity of work* the number of annual working days; and
- *Information intensity* the number of monthly hours dedicated to information through reading magazines, watching video documentaries, participating in conferences and using other information tools.

Perceived complexity is measured through the following six variables [which were rated using a Likert scale ranging from 1 (totally disagree) to 5 (fully agree)], evidencing the potential effects of PAT adoption:

- *Cost outcome (co)* the introduction of a PAT makes the farm more efficient by reducing the level of costs;
- *Managerial outcome (mo)* the introduction of a PAT makes farm management more complex, thus raising the required managerial skills;
- *Organizational outcome (oo)* the introduction of a PAT may bring about difficulty in achieving organizational and structural adjustments;
- *Production outcome (po)* a PAT requires changes in current agricultural practices;
- *Financial outcome (fo)* a PAT calls for difficult-to-recover financial investments; and
- *Imitation outcome (io)* PATs are not widespread in the area in which the farmer operates.

To discover the relationship between the variables belonging to the same theoretical construct, a correlation analysis was first carried out. The results show that the six variables are interrelated with significant Pearson correlation factors (< 0.01) (Table 1).

Therefore, given the presence of significant correlations, internal consistency was checked through the use of Cronbach's alpha. This index is a measure of reliability of a test, that is, how related a set of items is as a group. A high value of this index does not ensure that a scale is unidimensional, but we could test this point through exploratory factor analysis. The function of the standardized Cronbach's alpha is:

$$\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N + 1) \cdot \bar{c}}$$

Table 1 Correlation table of the perceived complexity variables

	Cost outcome	Managerial outcome	Organizational outcome	Production outcome	Financial outcome	Imitation outcome
Cost outcome	1	0.308[**]	0.351[**]	0.333[**]	0.341[**]	0.343[**]
Managerial outcome		1	0.730[**]	0.617[**]	0.541[**]	0.345[**]
Organizational outcome			1	0.627[**]	0.578[**]	0.347[**]
Production outcome				1	0.522[**]	0.434[**]
Financial outcome					1	0.344[**]
Imitation outcome						1

[**] Correlation is significant at the 0.01 level (2-tailed)

Table 2 Matrix components

Matrix components	
Cost outcome	0.557
Managerial outcome	0.827
Organizational outcome	0.846
Production outcome	0.815
Financial outcome	0.761
Imitation outcome	0.599

Table 3 Descriptive statistics of the "perceived complexity" indicator

	Minimum	Maximum	Mean	Std. deviation
Perceived complexity	− 2.49697	1.81111	0	1
	Skewness		Kurtosis	
	Statistic	Std. error	Statistic	Std. Error
	− 0.233	0.152	− 0.848	0.303

where N is the number of items, $\bar{c}$ is the average inter-item covariance among the items, and $\bar{v}$ is the average variance. This test shows a good result (0.832) that confirms the internal consistency between variables.

The existence of a significant correlation between the outcomes and a Cronbach's alpha greater than 0.8 raises the possibility of creating a synthetic indicator expressing the same information. To identify an indicator synthesizing the six variables of perceived complexity, a principal component analysis (PCA) was carried out. PCA is a technique for reducing the dimensionality of a set of data represented by a matrix X of size $n \times p$. In the PCA technique, the best possible way is to determine the linear combination of the original variables that maximizes a measure of variance. In other words, the PCA technique looks for a first linear combination with maximum possible variance, given some constraints. It then looks for a second linear combination that maximizes the variability given the constraints and the first component, and so on. In more formal terms, the first principal component for variables X_1 X_2, ..., X_p is the normalized linear combination

$$Z_1 = \phi_{11}X_1 + \cdots + \phi_{p1}X_p$$

which has maximum variability. The normalization refers to the constraint $\sum_{j=1}^{p} \phi_{j1}^2 = 1$.

The PCA extracted only one component (Table 2), which explains 55% of the variance.

The extraction of a component confirms the relationship between the different aspects and allows us to deepen the perception of complexity under a single indicator given by the PCA regressors. The descriptive statistics of the new indicator are as follows (Table 3).

Therefore, once the index has been created, it is possible to perform a two-step analysis.

Statistical model

To explore the probability of PA adoption, the conceptual framework used for the statistical analysis is presented in Fig. 2.

In the first step, a linear regression enables us to test the influence of socio-structural variables on the perception of complexity. The use of this model allows us to identify which elements are significant in the formation of the individual's perception during the adoption process (Folorunso and Ogunseye 2008). In the second step, a multinomial logistic analysis allows the significant aspects in determining the 3 types of agricultural entrepreneurs (adopters, non-adopters, planners) to emerge. In our paper, we identify "adopters" as farmers who have already engaged in the innovation adoption process. As a consequence, with reference to precision farming tools, the adopter group includes farms that have adopted at least one of the following technologies: precision fertilization, GIS maps, drones, precision plant production, precision tillage, precision weed management, precision sowing and sensors, and other technologies.

In contrast, "non-adopters" are not inclined to adopt innovations. Therefore, the non-adopter group includes farms that use traditional tools and do not want to adopt PATs.

Finally, "planners" are willing to adopt, but due to a set of constraints, they are unable to. Therefore, the planner group includes farms that now use conventional technologies but are planning to invest in PATs (Lencsés et al. 2014).

In summary, the index of perceived complexity is used as a dependent variable in a multiple linear regression, whose independent variables are farms' socio-structural factors. Linear regression is a method for estimating the conditional expected value of a dependent variable (Y), given the values of other independent variables, $X_1, \ldots, X_k$: $E[Y|X_1, \ldots, X_k]$. The multiple linear regression model is (De Lillo et al. 2007):

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \mu_i \qquad (2)$$

Each *X* represents 1 of the 6 outcomes explained above.

Before testing the linear regression, a correlation analysis was performed to demonstrate the absence of correlation between the socio-structural variables. The results of the correlation analysis are presented in Table 4.

From the table, a low correlation emerges (lower than 0.6) among the socio-structural variables. Consequently, we move to the second step of the analysis, with the aim of estimating the probability of PA adoption. Predictive models such as logit (Daberkow and
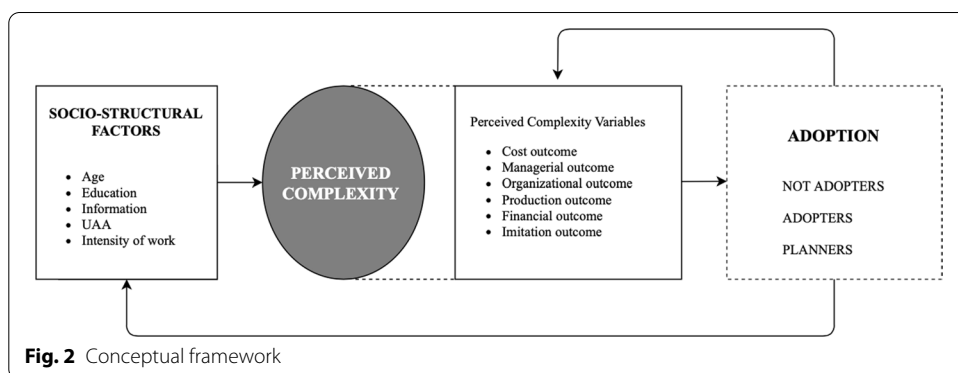
Fig. 2 Conceptual framework

Table 4 Correlations between socio-structural variables

	Farm size (ha)	Intensity of work	Age	Education	Intensity of information
Farm size (ha)	1	0.427	− 0.032	0.329	0.364
Intensity of work		1	− 0.199	0.315	0.463
Age			1	− 0.011	− 0.311
Education				1	0.427
Intensity of information					1

McBride 2003b; Larson et al. 2008; Khanna 2001; Isgin et al. 2008), probit (Walton et al. 2010; Roberts et al. 2004) or Tobit (Fernandez-Cornejo et al. 2001) are commonly used in the literature. Alternatively, theoretical models such as the TAM (Adrian et al. 2005; Rezaei-Moghaddam and Salehi 2010), SEM (Adrian et al. 2005) or factorial design (Hudson and Hite 2003) are privileged. In our analysis, we chose a logistic multinomial model with a trimodal dependent variable to be able to characterize the entrepreneurs into 3 categories (adopters, planners, non-adopters). Multinomial logistic regression is a classification method that generalizes logistic regression to multiclass problems (with more than two possible outcomes) (Schawb 2002; Christensen 1990). This model is used to predict the probabilities of the different possible outcomes of a dependent variable, given a set of independent variables (De Lillo et al. 2007). The independent variables are the 6 components of the perceived complexity index. Our aim is to understand whether these variables are significant in predicting the behaviour of the 3 types of entrepreneurs.

Results

The farmers included in the survey have an average age of 41. The average farm size is 57.02 ha, which is larger than the Italian national average (approximately 10 ha). Additionally, there is a medium–low work intensity; in fact, 62% of the samples indicate less than 50 working days per year. Farmers' level of education is medium–high; more than 50% of them have degree or postgraduate studies, and 75% dedicate between 4 and 12 h per month to improving their degree of information through magazines, conferences and videos (Table 5).

During the survey, the respondents were asked whether they were already adopters of PATs. Those who stated that they would not adopt were asked about their willingness to adopt in the future. Based on their answers, three different groups of farmers were identified: adopters, planners and non-adopters (Fig. 3). The three groups show different characteristics (Table 5).

The adopter group is characterized by young farmers with an average age of 37 years and with a high level of education; in fact, more than 75% are university graduates. More than 80% of those in the group indicate that they inform themselves frequently, more than 8 h per month. The farms have a high average size (104.6 ha), and 80% have a work intensity of more than 50 days per year. Due to the background of those in this group, combined with the high frequency of information and the experience of using PATs on their farms, these individuals are aware of the potential of innovations. Farmers who are not willing to adopt are 44 years old on average and are characterized by

Table 5 Characteristics of the sample

Variables	Total sample	Non-adopter	Planner	Adopter
Age (mean)	41	44	41	37
Farm size (ha) (mean)	57.02	25.8	42.7	104.6
Education				
Middle school	4.67%	12.86%	1.85%	1.27%
High school	38.91%	60.00%	38.89%	20.25%
Bachelor's degree	25.68%	17.14%	26.85%	31.65%
Master's degree	30.74%	10.00%	32.41%	46.84%
Intensity of information				
Less than 4 h per month	20.62%	38.57%	16.67%	10.13%
Between 4 and 8 h per month	35.02%	41.43%	50.00%	8.86%
Between 8 and 12 h per month	30.74%	17.14%	25.93%	49.37%
More than 12 h per month	13.62%	2.86%	7.41%	31.65%
Intensity of work				
Less than 25 days per year	28.79%	57.14%	26.85%	6.33%
Between 25 and 50 days per year	33.85%	28.57%	51.85%	13.92%
Between 50 and 75 days per year	23.35%	11.43%	19.44%	39.24%
More than 75 days per year	14.01%	2.86%	1.85%	40.51%

Fig. 3 Type of farmer
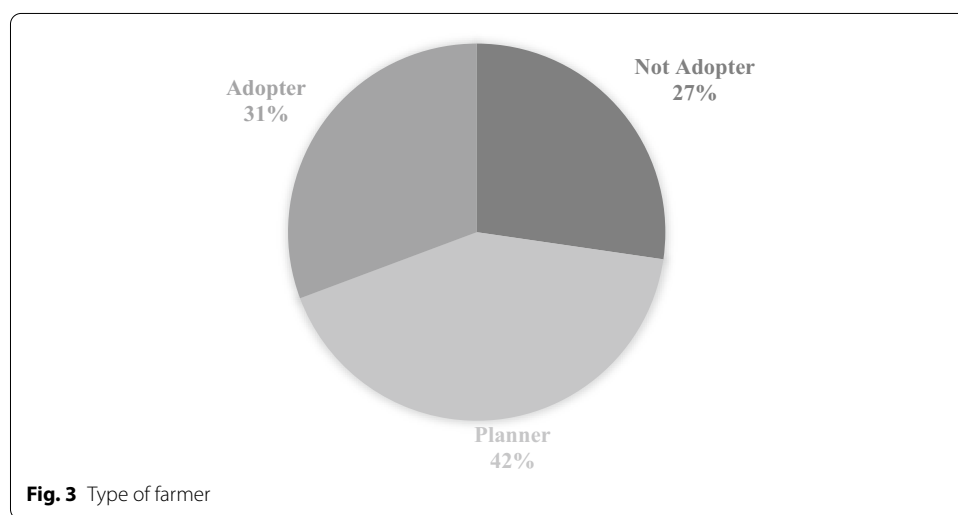
a medium level of education. In fact, more than 70% of the respondents in this group do not have a degree. The size of the farms of those belonging to this group is smaller than that of the farms of those belonging to the other groups (25.8 ha), these farms have a low average work intensity. The respondents stated that they had no particular interest in finding out about activities through magazines, videos or conferences; in fact, 80% of them spent less than 8 h per month on these activities. These farmers are not interested in adopting innovative tools even in the future. The planner group can be considered an intermediate group between the other two groups. In fact, these respondents have an average age of 41 years and run farms with an average size of 42.7 ha and with a high average work intensity (25–50 days per year for more than 50% of the group). In this group, education is not a characteristic element; in fact,

Table 6 Results of regression analysis

Variables	Unstandardized coefficients		Standardized coefficients	t	Sign	Collinearity statistics	
	B	Standard error	Beta			Tolerance	VIF
(Constant)	− 0.071	0.247		− 0.288	0.774		
Farm size (ha)	− 0.002	0.001	− 0.111	− 2.113	0.036*	0.753	1.328
Intensity of work	− 0.138	0.053	− 0.142	− 2.581	0.01*	0.694	1.44
Age	0.031	0.004	0.399	8.14	0*	0.87	1.149
Education	0.02	0.057	0.018	0.352	0.725	0.762	1.312
Intensity of information	− 0.342	0.06	− 0.328	− 5.657	0*	0.622	1.607

* significant at the 0.05 level (2-tailed)

Table 7 Test of multinomial analysis

Model	Model fitting criteria		Likelihood ratio tests	
	− 2 Log likelihood	Chi-square	df	Sig
Intercept only	459.387			
Final	314.351	145.036	12	0.000
Pseudo R-square				
Nagelkerke	0.540			

its level is heterogeneously distributed. The propensity to adopt, however, is demonstrated by a timid willingness to access information. In fact, 75% of those in the group dedicate between 4 and 12 h per month to activities that are useful for improving the knowledge of the potential of precision agricultural tools.

The results of the first step are presented in Table 6. The model, a stepwise regression analysis, highlighted how 4 out of 5 socio-structural variables are significant in determining the variation in farmers' perception of complexity. The only variable that is not significant is the level of education. A collinearity test was also carried out, with a maximum value of 12, which is less than the recommended value of 15. Therefore, we could demonstrate that there is no collinearity.

Once the relationship between socio-structural variables and perceptions has been investigated, we move on to the second step of the analysis, i.e., the multinomial model. This model allows us to predict whether the individual is an adopter, a planner or a non-adopter, based on the values they expressed regarding the perception variables. The test is robust and significant (Nagelkerke is used for the R framework), and in its use as a predictive method, it correctly classifies 64.4% of cases. The results are shown in the following table (Table 7).

To run the multinomial model, the reference category is the adopter (size: 79) to appreciate the differences that exist between adopters, planners and non-adopters (Table 8).

Compared to adopters, non-adopters show statistically significant differences in 5 out of 6 aspects. In particular, the significant variables are the efficiency outcome, managerial outcome, production outcome, financial outcome, and imitation outcome. Furthermore, the discriminating factors between adopters and planners are only 2 of the analysed variables, namely the financial outcome and imitation outcome. The analysis of Exp(*B*) permits us to

Table 8 Multinomial analysis

	Std. error	Sig	Exp(*B*)
Non-adopters (Size: 70)			
Intercept	1.761	0.000	
Cost outcome	0.234	0.000*	2.558
Managerial outcome	0.328	0.005*	2.400
Organizational outcome	0.371	0.612	0.829
Production outcome	0.313	0.016*	2.130
Financial outcome	0.307	0.000*	3.705
Imitation outcome	0.375	0.000*	5.755
Planners (Size: 108)			
Intercept	1.192	0.000	
Cost outcome	0.204	0.267	1.253
Managerial outcome	0.276	0.530	0.841
Organizational outcome	0.295	0.828	0.938
Production outcome	0.235	0.951	1.015
Financial outcome	0.229	0.000*	2.340
Imitation outcome	0.286	0.000*	2.937

* significant at the 0.05 level (2-tailed)

Table 9 Average intensity outcome

	Cost outcome	Managerial outcome	Organizational outcome	Production outcome	Financial outcome	Imitation outcome
Non-adopter	2.97	3.96	4.11	4.20	4.46	4.34
Planners	2.21	3.84	3.88	3.71	4.19	4.00
Adopters	1.62	3.32	3.29	3.04	3.18	3.23

quantify the probability of being an adopter with respect to being a non-adopter and the probability of being an adopter compared to that of being a planner. In the case of adopters—non-adopters—the average Exp(*B*) of significant factors is 3.31, while for adopters—planners—it is 2.64. It is important to point out the differences between non-adopters and planners. The significance of the initial investment cost factor is evident only for those who do not intend to adopt, while for planners, this aspect is not perceived as problematic. The same is true for the factor of difficulty in managing and changing cultivation practices. What planners and non-adopters have in common are the financial and imitation outcomes, which are significant for both. However, it decisively emerges that the Exp(*B*) for planners is clearly lower than that for non-adopters, demonstrating how the intention to adopt already lowers the perception of complexity with regard to these aspects.

To appreciate the different intensities, Table 9 shows that the average of the perceived complexity variables, measured through the use of a Likert scale, decreases in the transition from non-adopter to planner to adopter.

Discussion

This paper provides a new approach, grounded in the FACOPA model, under the hypothesis that perceived complexity plays a key role in affecting the propensity to innovate. The relevance of complexity in analysing innovation adoption is clearly demonstrated in our empirical analysis.

The paper has two main limitations. First, the farmers selected during the fairs were already aware of PA. This may represent a limit regarding the representativeness of the sample and an obstacle to generalizing the results (Taherdoost, 2016). The second limitation is that PA was studied as a single entity, without considering the variety of precision farming tools. At the same time, the purpose of the present work is coherent with Doloreux et al.'s (2009) perspective, that is, to analyse innovation systems as multidimensional, overcoming the technical connotation deriving from the technological dimension. Moreover, given the proposed theoretical framework, the modelling used may suffer from endogeneity problems, which did not arise in this case. This aspect represents a future research direction for verifying the possibility of using different statistical models.

Despite these limitations, this study has to be considered a step forwards in exploring the relevance of perceived complexity in technology adoption. On the basis of the analysis, some interesting results emerge. The first, not surprising, result shows that socio-structural variables influence the individual's perception of complexity, confirming most of the recent literature. The youngest farmers present the lowest values of perceived complexity. Furthermore, farm size and the intensity of work contribute to determining perceived complexity. As underlined in other studies, the largest farms with high labour intensity have lower levels of perceived complexity (Barnes et al. 2019). This may raise risks of an "elite capture" of benefits from the uptake of PA (Birner and Anderson 2009). The social context and relational assets are shown to have paramount importance. In fact, the higher the "informational exposure" of the individual is, the more the perception of complexity decreases, confirming other studies on the relevance of information in technology adoption studies (Kabunga et al. 2012). Informational exposure reveals the coherence of knowledge transfer systems. As a consequence, a widespread diffusion of farm advisory services in rural areas is required, with the purpose of providing sound and pertinent knowledge (EC 2017).

In the second step of the statistical analysis (the multinomial model), we borrowed Roger's distinction of three types of farmers with different inclinations towards PA by providing interesting insights and an original contribution grounded in the concept of perceived complexity. To the best of our knowledge, few studies have measured the dimensions affecting perceived complexity in a sound statistical way. By discriminating the three classes of farmers (adopter/planners/non-adopters), it is possible to detail perception and, consequently, better target policy actions. As deeply recognized in the literature, farmers are constrained by economic and technical barriers. The asymmetry between costs and benefits is an obstacle, especially for small-medium farms, which have less access to credit. The costs are also linked to the phase of implementation, where changes in the machinery are required and for which training is essential for the use of PA (Aubert et al. 2012). Furthermore, compatibility with a new technology is an important condition of adoption. Changes in the production process or in farm management

can lead farmers to not adopt (Aubert et al. 2012; Bessant et al. 2014). However, the relational context seems effective in shaping perceived complexity and in discriminating categories of farmers. Their decision could also be influenced by contacts with other actors of the value chain or trusted friend who have decided to adopt (Edward-Jones 2006; Joffre et al. 2018). The presence of financial resources and the evaluation of the experience of other farmers are components explaining most of the variation in the willingness to adopt PATs. As shown in Table 6, these two components are relevant for planners and even more relevant for non-adopters, as underlined in previous studies. This brings about a clear distinction in the behaviour among the surveyed farmers:

a. adopters/non-adopters. The empirical model clearly demonstrates that all complexity dimensions are relevant and significant in shaping a negative perceived complexity in non-adopter farmers. Therefore, non-adopters encounter barriers that are too high in all the considered dimensions (economic, organizational, financial, relational, etc.). We can label this "*full perceived complexity*" since the considered variable affects the perception and, consequently, hampers innovation adoption.

b. adopters/planners. On the other hand, the statistical model shows how planners seem to have overcome all the technical difficulties and barriers linked to the change in cultural practices that the innovation is going to bring about. Nonetheless, perceived complexity due to initial investments and to the so-called imitation outcome (low rate of adoption in the territorial agricultural system) emerges.

Conclusions

Grounded in the idea that perceived complexity results from the combination of multiple factors, this paper contributes to the recent literature. Authors have investigated variables affecting the perception of complexity and how they influence the probability of being a PA adopter or not. The FACOPA model allowed us to discriminate different degrees of propensity to adopt based on perceived complexity. As a consequence, the policy implications need to be split for the different categories of farmers. If, on the one hand, non-planners call for a wider set of policy tools, ranging from financial aid and informational and technical support through farms' advisory services, on the other hand, targeted policies should remove "last" obstacles. These policies should encourage planners to become adopters through financial aid and through the activation of innovation networks that lead to the creation of innovative milieus (Crevoisier 2004). Context-related variables also play a relevant role by creating positive "cultural" environments that are able to favour innovation adoption. The consolidation of positive experiences, such as European innovation partnerships, is a clear example of how a territorial system of innovation may engender both geographical and organizational proximity (Rallet and Torre 2004). Therefore, the analysis has relevant policy implications in that it provides the possibility of acting along two different levels: socio-structural and perception variables. Doing so results in more targeted policy goals, with the purpose of encouraging the adoption of PA and boosting the environmental and economic benefits for farmers. Recent EU documents on the new programming period (2021–2027) put information and knowledge among the cornerstones of the new development strategy. Information

and knowledge, if spread and adopted in both sound and pertinent ways, could represent a turning point in the acceleration towards new rates of adoption of technologies that allow more sustainable production and new ways of facing complexity in the adoption of precision agriculture tools.

Declarations

Competing interests
The authors declare that they have no competing interests.

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