

Article

Social Networks as Drivers for Technology Adoption: A Study from a Rural Mountain Area in Italy

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Abstract: Innovation processes includes social and communicative elements. The role of innovative technology for the development of farming systems is investigated in literature, but only a few studies deal with the influence of networks on the adoption of technologies by farmers. The aim of this paper is to verify if the adoption of smartphones for professional reasons by farmers is influenced by the networks to which farmers belong, the socio-demographic characteristics of the farmers, and their farm’s size. The case study is in the Valtellina valley, a rural mountain area in the north of Italy, where 53 livestock farmers were interviewed. The methodology is based on two steps. First, social network analysis is applied to diagnose the relationships of farmers in terms of connectivity and closeness and to detect the centrality measures of farmers in three different social relationships: production networks, market networks, and information exchange networks. A multiple linear regression model is then applied to test whether centrality measures of the three networks, the farmers’ socio-demographic characters, and the farm’s features drive the adoption of smartphones for professional reasons. Results suggest that the centrality measures in production networks positively drive the adoption of smartphones, while the centrality measures of market and information exchange networks do not have the same effect. At the same time, the farmers’ age negatively affects the use of smartphones for professional reasons, while the size of the herd, and the education and gender of farmers have no significant influence. The study contributes to the debate around the Agricultural Knowledge Innovation System and supports local policies based on the inclusion of farmers in the technological development in rural areas.

Keywords: social network analysis; smartphone adoption; farmers; interviews; Italy

1. Introduction

In 2010, the European Union included the concept of “smart” in its growth strategy Europe 2020, declaring that the European economy should pursue smart, sustainable, and inclusive economic growth [1]. Since then, the concepts of smart, sustainable, and inclusive development have been used to delineate the strategy to reduce regional disparities among the economic centers and the marginal areas of Europe. While the term sustainable generally refers to the topics of green economy, infrastructure and climate change mitigation, the concepts of smart growth and smart specialization relate to the policies that pursue a sustainable development by promoting R&D, innovation, knowledge, and learning [1]. In the contexts of rural areas, the European Commission is engaging with several initiatives for spreading the smart growth in these areas. Smart Villages for example are defined as “communities in rural areas that use innovative solutions to improve their resilience, building on local strengths and opportunities. They rely on a participatory approach to develop and implement their strategy to improve their economic, social, and/or environmental conditions, in particular by mobilizing solutions offered by digital technologies” [2].

At the same time, the European Commission is including the Agricultural Knowledge Innovation System (AKIS) approach in the post-2020 Common Agricultural Policy (CAP) as a strategy to foster the resilience of farming systems and support the development of rural areas through the widespread diffusion of knowledge and innovation technologies. The AKIS 1.0 strategy recognized that a great diversity of people is involved in creating agricultural knowledge and that it is necessary to include all the different stakeholders operating in rural areas and in the agricultural sector, such farmers, institutions, technicians, researchers, and so on. The AKIS 2.0 goes further, and aims at “building a future knowledge exchange system adapted to farmers’ needs” [3], based on an inclusive peer-to-peer learning, which leads to a co-created knowledge [3].

According to literature, the AKIS approach emerged as a critique of the linear models of innovation [3,4]. In the linear model of innovation, the innovation is centralized in strictly defined disciplines, driven by the research, and transferred from scientists to farmers [4]. With this approach, scientists are the innovators and farmers just the adopters of the innovation produced. On the contrary, in the AKIS approach, the innovation process is based on participatory research where different scientific disciplines and stakeholders jointly work together in a collaborative way to find new solutions to the farmers’ needs [4]. Innovation is hence driven by farmers’ requests for innovation and farmers, scientists, technicians, and other stakeholders are all the innovators. In this perspective, farmers are the first experimenters of the innovation, which is then modified and adapted to better respond to farmers’ needs [4]. Following Röling (2009) [5], the AKIS approach aims to study “the links and interactions between persons and/or organization that engaged in the process of generation, transformation, transmission, storage, diffusion, and utilization of knowledge and information, with the purpose of working synergistically to support decision making, problem solving, and innovations” [5].

According to the European Commission (2018) [3], understanding the “farmer-to-farmer knowledge exchange” is essential in developing innovative solutions that effectively improve the farming system. For this reason, several studies focusing on AKIS rely on social network analysis (SNA) [4,6]. Social network analysis (SNA) is the formal process of studying the social relationships among the actors and the social structure that emerges from the interactions in a group of actors. The SNA applies the graph theory to social relations [7,8] and is not just a methodology to describe relationships, but is also a quantitative method to provide measures on the overall structure of the social relationships in the system [7]. SNA has gained attention as a useful instrument to examine the diffusion of knowledge and innovation in different economic sectors, including farming systems analysis. The purpose of this study is to verify whether the adoption of smartphones for professional use by farmers is affected by the networks in which they participate, their socio-demographic characteristics, and the farm’s size. In the next sections, the theoretical background connecting the SNA and the technology adoption will be exposed, with a focus on the benefits coming from the usage of smartphones in the farms. Then, the methodology section will present the case study and the methods used to develop the analysis. The third section will describe the main results of the analysis, which will be discussed in the fourth section.

The Influence of Social Networks on Technological Adoption

According to literature, innovation is also a social and communicative process [8]. For this reason, the analysis of the interaction between actors and the exchange of information among individuals is a key element for understanding how the innovation is processed and adopted [9,10]. According to literature, even the innovation’s growth and performance is shaped by the structure of the network that groups its users [9].

In farming system analysis, several scholars have theorized that farm innovation is influenced by the social networks in which farmers are embedded. In fact, networks are used by farmers to find support and for knowledge exchange [11,12]. According to Murdoch (2000) [13] the network perspective also supports the sustainable territorial development of rural areas [13]. In particular, scholars invite to use the network approach in the agro-food system analysis [14]. While a vertical

“supply chain” approach helps to consider the balance of power between the actors in the supply chain, the horizontal “network” approach supports the qualification of these relationships [15].

According to literature, SNA based on the graph theory is a valid methodology to identify the relationships among actors [16–18]. Empirical analysis of farming systems has shown that farmers are integrated in multiple kinds of network, such as family, friends, and other farmers [17], which may all have a different impact on the farmer’s action and performance. At the same time, farmers relate with different public and private bodies, such as organizations, associations, institutions, and so on [6,12,19]. According to studies, the networks of peers seem to have a stronger impact on the farmers’ decision-making than the technical support, the networks between family members [11,17], or organization communities [20]. Oreszczyn et al. (2010) [20] further highlight the importance of understanding which actors are the key actors of a specific social network that facilitate the spread of information, and what makes them such key actors.

Analyzing the farmer-to-farmer SNA, Aguilar-Gallegos et al. (2015) [21] show that the farmers with the higher amount of connections with peers had also higher levels of technology adoption, which further led to higher revenues. At the same time, farmers participating in collaboration networks are more prone to adopt technological improvement [22]. According to Ramirez (2013) [22] the inclusion of SNA data in the technology adoption analysis provides information about the influence of knowledge flows on technology adoption that classic drivers of adoption such as age, education, and landholding size, while valuable, do not explain [22].

Up to now and to the best of our knowledge, no study has been conducted on the influence of networks on the use of smartphones by farmers, despite the fact that the literature has concluded that social pressure plays a determinant role on the adoption of smartphones for professional usage [23]. According to literature, the diffusion of smartphones is not only driven by the development of technological infrastructures, but also by the actor’s social influences on the perceived usefulness among mobile users [24]. For this reason, the adoption and usage paths may be distinct for segments or groups in the overall population [24]. At the same time, Lee (2014) [25] highlights the influence of family and peers in the adoption of smartphones among youth, beyond the socio-demographic characters such as age and gender.

Smartphones are relevant professional tools, since they offer a higher multi-functionality than mobile phones. They are portable devices that integrate communication, information, and data management functions. In fact, they combine functions previously performed only by cellular phones, such as voice-call, SMS, and camera functions, and functions deriving from desktop computers, such as the storage and organization of information, the access to web browsers and e-mail, and more generally the ability to process and share data [26]. Especially, they offer the possibility to install applications depending on the user needs.

Despite the widespread adoption of smartphones in everyday life, few studies have been undertaken on the usage of smartphones for professional reasons by farmers. Jelinsky et al. (2019) [26] highlight the discrepancy among the number of people aged under 35 owning a smartphone (94%) and the percentage of livestock farmers of the same age using it for professional reasons (58%). They suggest that in case of livestock farms, new hardware and software improvements may lead to an increased perception of their usefulness among farmers. In the same study, they claim that understanding the determinants of adoption is important to improve the user acceptance and thus its effective usage. Smartphones are relatively cheap technologies that offer to farmers the possibility to have at their disposal more needs-tailored apps that cover different aspects of the farming activity, thus supporting their decision-making with a systemic perspective. Smartphones also offer the possibility to integrate with other technologies, such as milking robots or other precision agriculture technologies. In this sense, they act as an intermediate technology between others, collecting and processing different data about the farm. A greater use of them thus facilitates a more widespread use of data-driven software, further improving the digitalization of agriculture. The smartphones’ apps are also rapidly evolving innovations that develop and adapt considering the immediate feedbacks users provide to the software

developers. In this sense, smartphones are suited to the AKIS approach that claims a co-evolution of innovation.

Nevertheless, as in the case of other technologies, the spreading of smartphones can be hampered and can be a further source of social exclusion for specific people. According to literature, age, education, geography, and the personal aptitude of the farmer may be factors that prevent farmers from adopting technology and further exclude them from production improvement [27,28]. To develop and offer more needs-tailored apps and to spread the digitalization of agriculture, it is thus crucial to understand the drivers for smartphone adoption.

2. Materials and Methods

The analysis is based on two steps. In the first step, the social network analysis (SNA) is applied first by defining the networks between farmers and then by the application of several variables that quantify and characterize the networks. In the second step, a multiple linear regression analysis is applied to test whether the data coming from SNA and the data coming from interviews regarding the socio-demographic characteristics of farmers and their farm's features can be drivers for the usage of smartphones for professional reasons. Both SNA and multiple regression analysis were performed using the R software version 3.2.3; in particular, the SNA was performed using the *igraph* and *ggplot* packages.

2.1. Case Study

The case study is a rural remote mountain area in the Italian Alps in the Lombardy region, close to the border with Switzerland (Figure 1). The area includes the valleys of Valtellina, Valchiavenna, and Alto Lario. The area has been included in the Italian National Strategy for the “Aree Interne” (Internal Areas). The policy is applied in remote areas that, although distant from the main services' centers, are provided with several cultural, social, and environmental resources, which constitute the base to pursue a development strategy. In the framework of the regional Rural Development Program (RDP), the entire area has been classified as a “rural area with complex development problems”.

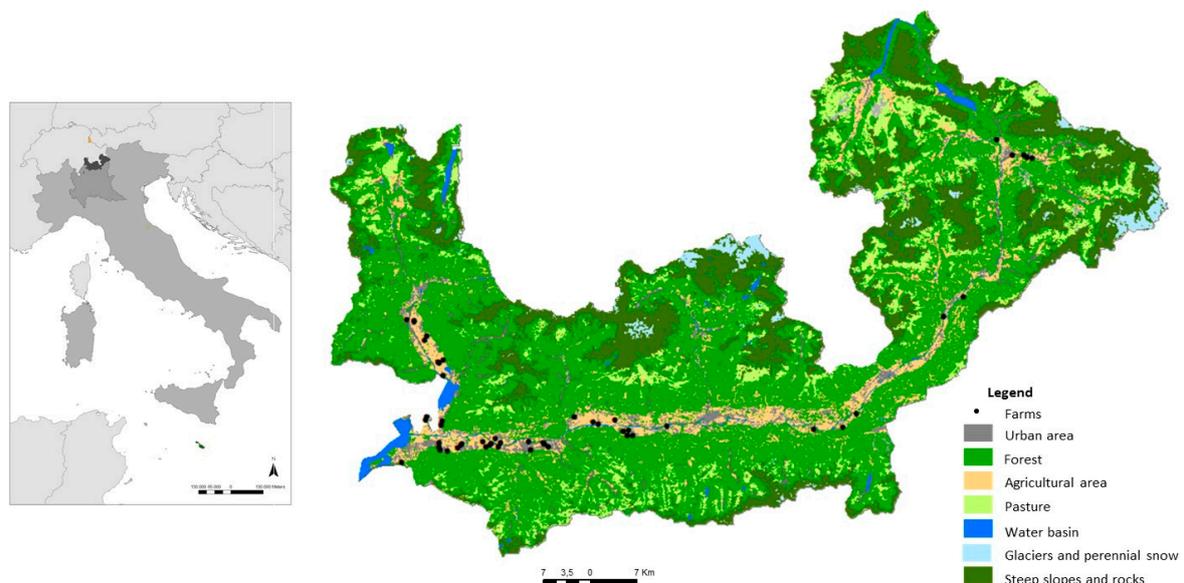


Figure 1. Case study.

The area is characterized by a specific geographical formation: its altitude varies from around 198 m to around 4000 m above sea level, and it has a relevant east–west extension of 3212 km². More than 70% of the provincial territory is located 1500 m above sea level, and only a small portion,

just over 1%, is urbanized. As it is possible to observe in Figure 1, most of the area, which includes the entire Province of Sondrio, is composed of natural and forest areas (88%), while the agricultural area covers only 7.4% [29]. As is typical of the alpine landscape, agriculture is performed both in the valleys, where it is characterized by the presence of stable meadows interspersed with cultivated fields such as corn for fodder production, and at higher altitudes, where the farming system is based on pastures (“alpeggio”) that characterize the rural landscape. The mountain pasture and the livestock production represent a fundamental element of the local identity and cultural heritage that policies try to protect and enhance. On the one hand, it constitutes an economic value, because it allows the creation of high quality agro-food products, and it allows the expansion and diversification of the tourist offer of the area. On the other hand, it plays a very important role in environmental conservation and the mountain landscape. In recent decades, however, the decrease of the number of farms and the concentration of animal husbandry in the valley have led to a decline of the pastures. Nevertheless, the integration of the valley’s agriculture and mountain pastures based on livestock farming systems still represents an important cultural and identity trait, an economic value, and an environmental and naturalistic heritage for the whole territory [30].

In 2011, in the last national census [31], the livestock farms represented 44% of the total farms, a percentage that is higher than the regional value (41%). Despite its economic importance, the number of livestock farms have decreased from 1982 to 2010 by an average of 35%, one of the higher rates in the Lombardy region and especially in the last decade. The decreasing of livestock farms concerns sheep farms (−88%), poultry (−81%), and pigs (−55%), while dairy farms showed a minor decrease (−38%). In the case study, the decreasing of farms is not accompanied by a similar decrease in the number of animals, confirming a general trend towards the increasing of the farm size. The decreasing of cows is about 10%, the lowest rate considering the decrease in the number of pigs, sheep (−29%), and poultry (−32%) in the last decade. These data confirm the importance of bovine dairy farms for the local rural economy. According to the estimates, livestock products in the area accounted for about 63% of the gross saleable product. The agricultural economy of the region is based on several traditional products mainly connected to the livestock productions and commercialized in national and international markets: the *Bresaola* ham and several cheeses such as *Bitto* and *Casera* [32]. To highlight the importance of traditional and quality food for the local rural economy, the Lombardy region established the agricultural district “Valtellina che gusto!” in 2010 to promote the agricultural traditional production of the area [33].

2.2. Sample and Survey

In the area, 53 dairy farmers were interviewed in 2019 (Figure 1). Figure 1 shows the localization of the farmers interviewed. The farmers belong to two cooperatives: the Valtellina Social Cheese Factory (LSV) (35 members) and the Valtellina Dairy Cooperative (COL) (44 members). The two cooperatives have worked together since 2011, when LSV incorporated farmers’ members of COL in an effort to avoid the sale of COL to a multinational milk company. In this way, LSV expanded the company structure. The two cooperatives still exist, but they now share the collection of the milk from farmers, as well as the process and the sale of cheese. At the moment, the only difference between the two cooperatives is their geographical deployment: LSV members are located in the western part of the area, while COL members are mostly in the eastern side. Among the total 79 farmers, 26 farmers were excluded, because they did not have or did not use the smartphone for professional usage, and because they had goats rather than cows. The 53 farmers finally interviewed represent the 89% of the sample and cover the whole area of the case study (Figure 1).

A preliminary inquiry was carried out to test the questions and the survey’s indicators, and was submitted to five farmers, three belonging to LSV and two to COL. Then, the face-to-face interviews were carried out by two researchers and lasted 1 h each. The researchers met the farmers in their farm. The questionnaire was organized in three main sections. In the first one, the questions focused on the main socio-demographic characteristics of the farmers in terms of age, education, and gender.

The questions also dealt with the main features of the farms considering the utilized agricultural area and the number of animals by breed and age. Table 1 shows the main characteristics of both the farmers and the farms.

Table 1. Sociodemographic characteristics of the sample (n = 53).

Gender	n	%
Male	44	83
Female	9	17
Age	n	%
less than 40 years	16	30
40–54 years	22	42
55–64 years	11	21
over 65 years	4	8
Average (standard deviation)	46.46 (11.83)	
Educational Level Completed	n	%
Primary and Middle School	25	47
High School	24	45
University degree (bachelor and master)	4	8
Size of Farm	n	%
<50 lactating cows	32	60
50–100 lactating cows	15	28
>100 lactating cows	6	11
Average (standard deviation)	57.87 (54.13)	

Most of the farmers are male, aged between 40 and 54. Only a few of them have a degree, while the majority have completed middle school. The vast majority of farms are small farms. Small farms have on average 29 lactating cows. The bigger farms have on average 173 lactating cows, and the intermediate group have on average 71 cows. Female farm managers are concentrated in small and medium size farms, while the bigger farms are only managed by males. No difference in terms of age and education is found among farms with different sizes.

In the second section, farmers were asked the reasons why they were using smartphones for professional reasons. In this case, the specific question addressed to farmers was: “In your work, how often and for what reasons do you use your smartphone?” A list of potential reasons for the use of smartphones for farm management purposes was then proposed. Three reasons covered the search of information: (1) consultation of a weather app, (2) search for information via social media (Facebook, Twitter, etc.), and (3) search for information via the web. Three reasons covered the communication and the possible exchange of information with other farmers and with the cheese factory: (4) communication via WhatsApp with other farmers, (5) communication via email with other farmers, and (6) communication via email with the cheese factory. In the last case, the question specifically referred to the information exchange about the data on the quality of the milk, which are communicated mainly via email by the cheese factory. Farmers were asked to indicate the reasons why they were using their smartphones, indicating for each one the frequency of use on the basis of a Likert scale, ranging from 1 = “never” to 5 = “very often”. To increase the variability in the potential responses, there was also the possibility to mention any other reason not included in the list. Table 2 shows the main results of this section. The smartphone is used mostly to search information via the internet (about 46% of the respondents) and to consult the weather (about 70% of the respondents), which also provides information about other climate-related information and the spreading of animal manure. It seems to be less used for communication purposes. Social media are not used for professional purposes. The communication via WhatsApp with other farmers is used by 38% of farmers, while 35% of them stated that they have never used it for this scope.

Table 2. Main results relating the reasons to use the smartphone (n = 53).

	Consultation of the Weather App	Search for Information via Social Media	Search for Information via Internet	Communication via WhatsApp to Other Farmers	Communication via Email to Other Farmers	Communication via Email to the Cheese Factory
Never (%)	22.64	56.60	33.96	35.85	62.26	37.74
Rarely (%)	1.89	16.98	3.77	11.32	24.53	15.09
Sometimes (%)	3.77	15.09	15.09	15.09	9.43	24.53
Often (%)	9.43	3.77	24.53	22.64	1.89	9.43
Very Often (%)	62.26	7.55	22.64	15.09	1.89	13.21
Tot (%)	100.00	100.00	100.00	100.00	100.00	100.00
Average farmers scores *	3.87	2.70	1.57	2.45	1.89	2.98
Standard deviation *	1.68	1.53	0.89	1.42	1.25	1.61

* Note: values refer to the Likert scale.

It is important to mention that, in the sample, only three farmers have implemented a milking robot, and only these farmers said that they use the smartphone for checking the software of the robot. No GPS technologies are used by any farmer. The Internet coverage is good, with the exception of pasture fields in mountain areas.

In the third section, the questions concerned the farmers' networks. In the survey, three types of network were proposed: (1) production networks, (2) market networks, and (3) information exchange networks. Farmers were provided with the list of the farmers that were part of the sample, and for each farmer, they had to indicate the presence of the three types of relationship or not. In the case of the production relation, farmers were asked with which farmers they had shared production factors such as machineries, tools, workforce, and practical help on the farm more generally. In the second case, farmers were asked to which farmers they sold products such as farms' inputs or outputs like fodder, calves, or others. In the case of the information exchange network, farmers were asked which farmers they asked for advice, and which farmers' point of view they took into account and trusted more.

The results of this third section were then organized in a dichotomous matrix, one for each kind of network. In the matrix, the rows indicate each farmer interviewed, and each column indicates the farmers of the sample with whom he or she has the relationships. The value 1 was set if the farmer expressed the presence of the relation with a farmer, the value 0 indicated the absence of the relation.

2.3. Social Network Analysis

In the graph theory, a network is defined as a set of nodes joined by ties. The dichotomous matrix that expresses the presence (1) or absence (0) of the relationship between two nodes is called Affiliation matrix. This analysis is based on one-mode undirected networks. In a one-mode network, the nodes are all peers, while in a two-mode network the nodes are of different kinds. A network is undirected when the ties are links between nodes, while for a directed network, the ties are arrows, showing the direction of the relationship.

Following the literature [9,17] the SNA is focused on two levels of analysis. The first level is focused on the nodes, to understand the centrality of each actor. The centrality measures adopted in this study are the degree centrality and the betweenness centrality. They both identify the actors of the network with more power, but in different ways. The *Degree Centrality* measures the number of a node's ties by counting the number of connections (edges) it has to all the other nodes [34]. Thus, the central nodes are those with the higher amount of links. In literature, it is interpreted as a measure of the node's local connectivity and thus as a measure of the node's bonding capacity [9,17,21]. The betweenness centrality is defined as the share of times that a node i needs a node k (whose centrality is being measured) in order to reach a node j via the shortest path. In other words, it counts the number of times in which k is in the shortest path between other nodes [7]. In this respect, it is interpreted as a measure of the node's global network connectivity. It represents the number of times a node can act as a bridge between nodes. The nodes with the higher betweenness centrality measures are those that are also connected with subgroups of nodes or marginal nodes. In this way, their role can be at the same time to bridge groups of nodes or to act as broker, namely, to shut down the network flow if necessary [7,17]. In this regard, it is usually interpreted as a measure of the node's control over the flow of information in the network [7] and as a measure of the capacity to link together un-connected nodes [17].

The second level of analysis aims at detecting the main properties of the overall network. To do so, several indicators were applied in the study. The density is calculated as the ratio between the actual number of edges among nodes in a network and the maximum number of ties possible if all the nodes are connected. In literature, the density is used to measure the solidity and the cohesion among the actors of the network and thus as a measure of trust relationships [8,17,35]. At the same time, it is also interpreted as a measure of the network's closeness, as a completely connected network may also be a network less open to the inclusion of new members able to bring new information [8,17]. The Transitivity Index—also called the cluster coefficient—measures the capacity of the nodes to create sub-groups in the network. Specifically, it measures the probability that closed networks are also

connected. In other words, if a node i is connected to j , and j is connected to k , the probability that i is connected to k is defined by the transitivity index [9,17]. As in the case of the density, this index is used to define the capacity of actors to connect and at the same time close the network [17]. In the case of innovation diffusion, the clustering is interpreted in two different ways. On the one hand, it is associated with a high level of communication exchange between actors, implying that each node can have a high access to information, consistently with the density measure. On the other hand, a high level of clustering coefficient may also imply redundancy and inefficiency in the exchange of information. As in the example used before, if i is connected to j , and j is connected to k , then i does not need to connect to k to have the information. Thus, the link between i and k is redundant. With higher levels of transitivity, the single ties lose importance in the spread of information and the network is less efficient [8,9].

In graph theory, a connected component is a subgraph where there is a path between every pair of vertices. The giant component is the bigger component of the network. In the literature, it is used to determine the overall connectivity of the network [17]. Finally, the degree assortativity refers to the preference by the network nodes to attach to others nodes that are similar in some way [9]. It is operationalized as a correlation between two nodes in terms of degree centrality. The assortativity coefficient is the Pearson correlation coefficient of degree between pairs of linked nodes. Positive values of the coefficient indicate a correlation between nodes of similar degrees, while negative values indicate relationships between nodes with different degrees. In other words, when the coefficient is positive, the nodes have the tendency to connect to nodes with a similar measure in terms of degree centrality, while when the coefficient is negative, nodes tend to connect to nodes with different measures in terms of degree centrality. In this case, the network is defined as *disassortative* and it indicates the capacity of central nodes, which have higher degree scores, in a network to attach to distant nodes, which have lower degree measures. It thus can be considered as a measure of the capacity of the network to connect the periphery and the core of the network, thus as a measure of the overall connectivity.

3. Results

3.1. The Social Network Analysis of the Dairy Farmers

Figures 2–4 represent the three types of networks. As it is possible to see, in all the three networks, there are exchanges between the farmers belonging to the two cooperatives. The main difference is that while in the information exchange network, the central nodes connecting the two cooperatives are also the nodes with the higher degree (Figure 4), in the production network, the farmers with the higher degree are connecting mostly with the farmers belonging to the same cooperative (Figure 2). This can be explained by the fact that in the interviews, farmers indicated in the production network other farmers that were mostly neighbors, and as said, the two cooperatives have a different territorial coverage. Usually farmers ask for help in the fields' works, such as stacking the hay, sharing machineries, and working in the stable. They thus tend to ask for help from neighbors, as mountain areas are not densely populated due to the geographical conformation of the valleys. For this reason, the production network is also sparser than the information exchange network. On the contrary, in the information exchange network, geography seems to play a less determinant role (Figure 3). In this case, the central farmers were indicated by both far and close farmers and by farmers belonging to the two different cooperatives. Here, the reputation of each single farmer plays a defining role for connecting to him/her. Finally, the market network is highly disconnected (Figure 2). The sale of products is not a common practice between farmers. When it happens, the sale of product is especially focused on the sale of calves and fodder. Usually farmers sell the hay when they have a surplus of it, which is not usually the case, since the main element of the food ration in these farms is the fodder. At the same time, farmers are usually autonomous in their hay, so they need to buy hay from other farmers only in exceptional situations. Considering the sale of calves, in the interviews, we noticed a certain mistrust among farmers on the way other farmers from the valley and from their same cooperative were taking

care of their animals. For this reason, they usually prefer to look for calves abroad or in other regions in the north of Italy. A specific policy from the cooperatives was in fact applied to promote the sale of calves among the cooperatives' farmers to better control the quality of the animals and thus of the milk.

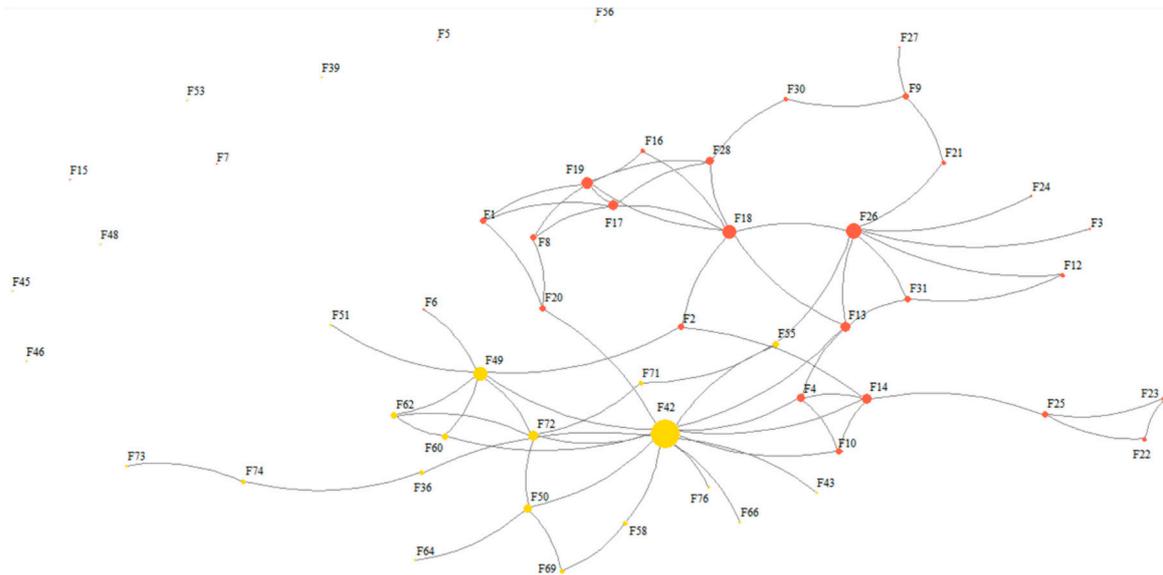


Figure 2. Production network. The size of the nodes represent the degree centrality for each node. The red nodes represent farmers from LSV; yellow nodes represent the farmers from COL.

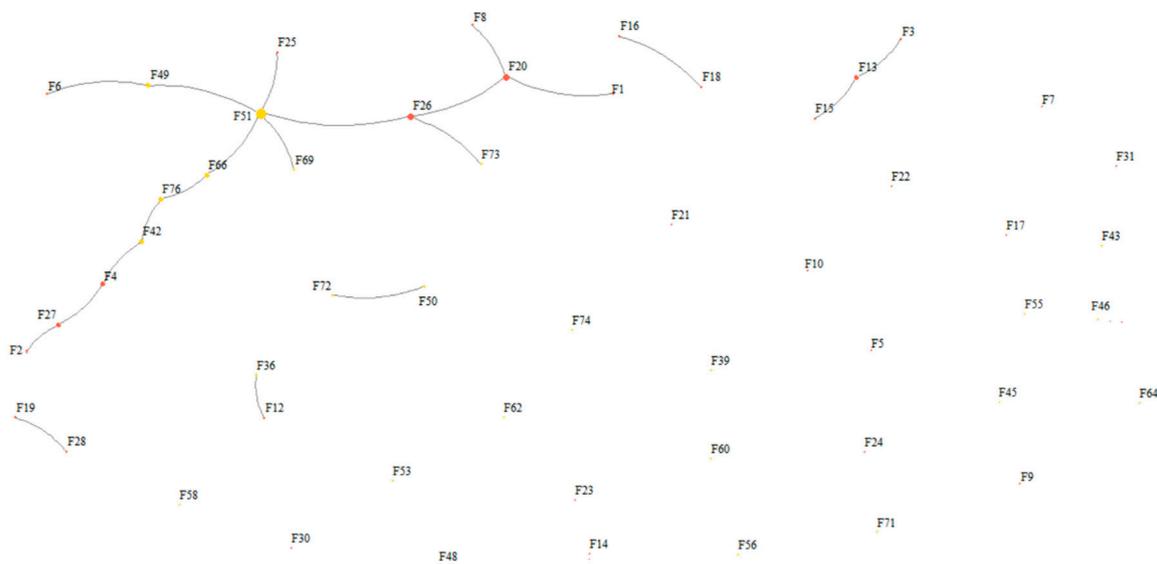


Figure 3. Market network. The size of the nodes represents the degree centrality for each node. The red nodes represent farmers from LSV; yellow nodes represent the farmers from COL.

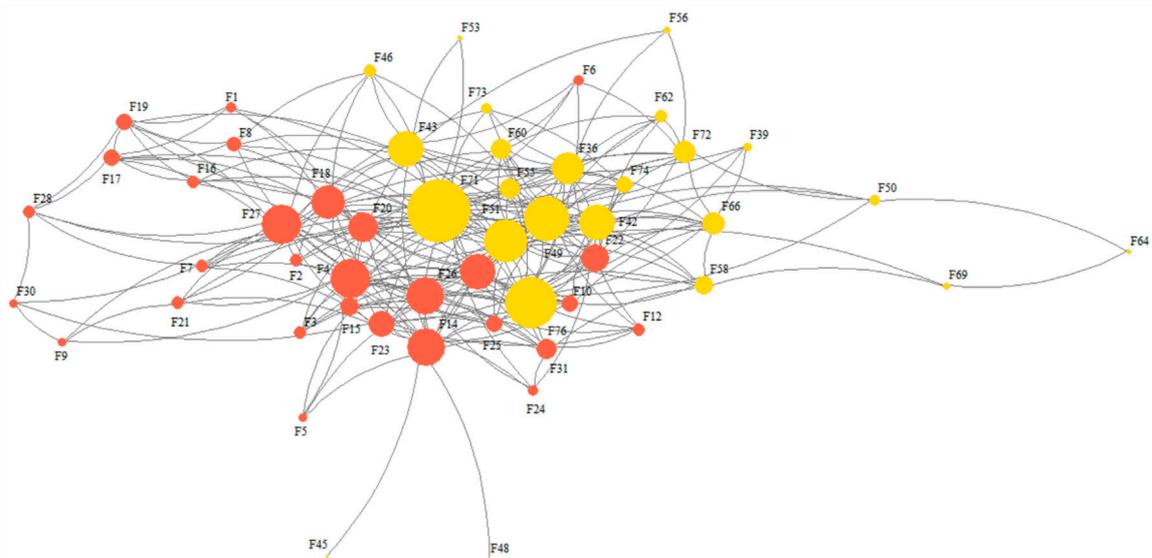


Figure 4. Information exchange network. The size of the nodes represent the degree centrality for each node. The red nodes represent farmers from LSV; yellow nodes represent the farmers from COL.

Table 3 shows the main properties of the developed networks. As it is possible to notice, the market network is a sparse network, which only groups 43% of the total sample, while the production network groups the 83% of the nodes, and the information exchange network is the one that is able to connect all the nodes (100%). The information exchange network also has the higher values in terms of density than the production and market networks. This result suggests that the information exchange network is more cohesive than the production network. At the same time, the value of the transitivity index of the production network shows a tendency of nodes to create clusters, which is not balanced by a high-density score, as it is in the case of the information exchange network. This result is consistent with the information derived from the interviews. For activities of production support, farmers tend to help each other in small groups of close farmers. At the same time, the assortativity coefficient is negative for both the production and the information exchange network, but the former is slightly more disassortative ($r = -0.23$) than the latter one ($r = -0.21$). This result suggests that, despite being sparser than the information exchange network, the production network shows a good connectivity in the overall network, being able to connect the nodes at the network's core with the nodes at the peripheries. The giant component groups 85% of the nodes, which is a high score considering the low value of density. This result is confirmed by the analysis of the centrality measures. In both cases, the nodes with the higher centrality degree also have the higher betweenness centrality, thus revealing that in both cases, the central nodes have the capacity to connect with sub-groups in the periphery. Nevertheless, this tendency seems to be more accentuated in the production network than in the information exchange network. Moreover, despite the lower density score, the average betweenness centrality of the production network is higher than the betweenness centrality of the information exchange network, again confirming a higher connectivity capacity. The average degree centrality in the production network is lower than the average degree centrality of the information exchange network, thus suggesting a higher local connectivity for the information exchange network. Nevertheless, the analysis of the standards deviation suggests a more homogeneous distribution in the production network.

Table 3. Network statistics and structural properties.

	Production Network	Market Network	Information Exchange Network
Number of nodes connected	44 (83%)	23 (43%)	53 (100%)
Number of edges	70	25	267
Degree—av. (st.dev.)	2.64 (2.60)	0.79 (1.03)	10.08 (7.04)
Top 5 nodes (degree score)	F42 (15), F26 (8), F18 (7), F49 (7), F19 (6)	F51 (5), F20 (3), F26, F13, F27, F42, F42, F49, F66, F76 (2)	F71 (32), F76 (26), F49 (23), F51 (22), F4 (20)
Betweenness—av. (st.dev.)	41.51 (86.05)	6.38 (16.31)	26.30 (44.34)
Top 5 nodes (betweenness score)	F42 (528), F26 (223), F18 (186), F13 (179), F14 (130)	F51 (79), F66 (50), F26 (47), F76(44), F42 (36)	F71 (224), F14 (128), F27 (106), F51(100), F71 (95)
Density	0.05	0.01	0.19
Transitivity	0.21	0	0.36
Giant Component (% of nodes)	44 nodes (83%)	5 nodes (9%)	53 nodes (100%)
Assortativity coefficient (r)	−0.23	0	−0.21

3.2. An Empirical Test on the Critical Factors to Use the Smartphone for Professional Use

The SNA provides interesting results about how actors participate in different networks and how this influences the structure of the network. To test if the network is a driver for the usage of smartphones for professional reasons, a multiple linear regression analysis has been applied. In particular, we developed three separated models for the three networks developed. In all the models, the dependent variable is the smartphones use for professional reasons, as explained in Section 2.

Following the theoretical argumentation previously introduced in Section 1, the centrality measures derived from the three networks developed were used as independent variables of the three models to explain the use of smartphones for professional reasons. The production degree centrality refers to the degree centrality in the production network; thus, it considers the centrality of the farmers in the production network. The market degree centrality considers the degree centrality in the market network, and finally the information exchange degree centrality measures the degree centrality of the nodes in the information exchange network. At the same time, the production betweenness centrality refers to the betweenness centrality of farmers in the production network, the market betweenness centrality considers the betweenness centrality in the market network, and finally, the information exchange betweenness centrality measures the betweenness centrality in the information exchange network.

Finally, controls variables were included in the models. These variables refer to the features of farms and individual characteristics of farmers. Among the control variables, the number of the lactating cows (LSU_milk) defines the production capacity of the farm, denoting its production size. The socio-demographic characteristics of the farmers help in considering the farmers' personal attitude toward smartphones. The models verify whether the age (Age), the educational level completed (Education, categorical variable where 1 identifies primary and middle school, 3 identifies the high school, and 5 identifies the university), and the gender (Gender, categorical variable where 1 identifies male and 2 identifies female) can be a factor for the use of smartphones for professional reasons. The descriptive statistics of the variables are included in Section 2.

The correlation matrix shows high correlations between the degree and the betweenness centrality variables for the three networks, and especially for the production network (Table 4).

Table 4. Correlation matrix.

Variables	1	2	3	4	5	6	7	8	9	10
1 Age		−0.30	0.06	−0.13	−0.03	−0.10	−0.03	0.00	−0.15	0.13
2 Education			−0.06	−0.09	0.04	0.30	0.07	0.03	0.66	0.03
3 Gender				−0.21	−0.27	−0.14	−0.04	−0.30	0.12	−0.04
4 LSU_milk					0.21	0.12	0.45	0.15	0.13	0.32
5 Production Degree Centrality						0.32	0.38	0.87 ***	0.23	0.17
6 Market Degree Centrality							0.51	0.31	0.83 ***	0.31
7 Information Exchange Degree Centrality								0.34	0.52	0.86 ***
8 Production Betweenness Centrality									0.27	0.14
9 Market Betweenness Centrality										0.35
10 Information Exchange Betweenness Centrality										

Note: Pearson correlation is measured for variables 1, 4, 5, 6, and 7. Polychoric correlation is measured for variables 2 and 3. *** denotes significance at 1%.

The formula (1) describes the multiple linear regression model applied, where y_i indicates the dependent variable, which is the use of smartphone for professional reasons; β_i indicates the intercept; x_i indicates the independent variables in the three model, which are the three degree centrality measures; and z_i indicates the control variables, notably the age ($z1_i$), the education ($z2_i$), the gender ($z3_i$), and the number of the lactating cows ($z4_i$).

$$y_i = \beta_i + x_i + z1_i + z2_i + z3_i + z4_i \quad (1)$$

Table 5 shows the results of the developed models, where the independent variables are the production network's degree centrality, the market network's degree centrality, and the information exchange network's degree centrality in Model 1, Model 2, and Model 3, respectively.

Table 5. Multiple linear regression with the dependent variable as the production centrality; LSU_milk refers to the number of lactating cows; Education 2 refers to the elementary school; Education 5 refers to diploma degree; Prod_deg_centr refers to the degree scores of farmers in the production network; Prod_deg_centr refers to the degree scores of farmers in the market network; and Info_deg_centr refers to the degree scores of farmers in the information exchange network.

Variables	Model 1			Model 2			Model 3		
	Coeff.	St.Err.	p Value	Coeff.	St.Err.	p Value	Coeff.	St.Err.	p Value
Intercept	3.95	0.58	***	4.01	0.60	***	3.99	0.60	***
Age	−0.04	0.01	***	−0.04	0.01	***	−0.04	0.01	***
Education 2	0.21	0.26	n.s.	0.27	0.26	n.s.	0.28	0.26	n.s.
Education 5	−0.29	0.49	n.s.	−0.58	0.52	n.s.	−0.39	0.50	n.s.
LSU	0.00	0.00	n.s.	0.00	0.00	n.s.	0.00	0.00	n.s.
Gender	0.18	0.32	n.s.	0.09	0.33	n.s.	0.05	0.33	n.s.
Prod_deg_centr	0.11	0.05	*						
Mark_deg_centr				0.18	0.13	n.s.			
Info_deg_centr							0.03	0.02	n.s.
R ²		0.39			0.35			0.34	
p value		***			**			**	

Note: *** denotes significance at 1%, ** at 5%, and * at 10%.

In all three models, age has a significant statistical negative impact on the use of smartphones for professional reasons (Table 5). In all the models, the age increase impacts −0.04 time a reduced adoption of the technology. The older the farmers are, the less likely they are to use smartphones for professional reasons. In contrast, for the three models, the use of smartphones for professional reasons

does not seem to be significantly affected by the size of the farm. Smaller or bigger farms have the same tendency to make use of the technology. At the same time, the gender and the education of farmers are also not significant factors in influencing the use of smartphones by farmers.

In contrast, the use of smartphones seems to depend on the network capacity of the farmer. Notably, the production degree centrality is the unique statistically significant variable among the centralities variables of the three networks. This result suggests that the local connectivity of the central nodes in the production network positively influences the use of smartphones, while in the market and information exchange networks, the central nodes do not play a significant role in spreading the technology. Considering the high correlation between degree and betweenness centrality in the production network (Table 4), the betweenness centrality also positively affects the use of the smartphone in the three networks. This result confirms that the same central nodes also have the bridging capacity to spread the technology in the production network, while it is not possible to state the same in the case of the other two networks.

Table 5 shows that the results on socio-demographic characteristics of the dairy farmers, such as age, gender, and education, and the farm size do not change among the three models. Nevertheless, from a relational perspective, the results among the models are quite different. From these results, we infer that the use of smartphones in our sample is influenced by the professional relationships, and it does not seem to be influenced by the market relations. Specifically, it does not seem to be influenced by relations of general advice and information exchange among farmers, even though by analyzing the three types of network, this last one seems to be more cohesive than the production network.

4. Discussion and Conclusions

The aim of this paper was to verify if the adoption of smartphones for professional reasons by farmers is influenced by the networks among the farmers, the socio-demographic characteristics of the farmers, and by the farm's size. Up to now, studies have investigated the drivers for technology adoption [26]. Considering that social interactions and the flow of information may drive the adoption of technology [22], this study goes beyond current literature, since it includes variables related to the social relationships of farmers.

Our results confirm that age can be a potential factor for the exclusion of farmers in the use of the technology, as several authors have claimed in literature [26], while surprisingly education is not a influencing factor. Even if literature found a significant positive connection between the size of farms and of the herds with the adoption of smartphones and technology [22,26], our study does not find the same result: small farms can have the same tendency to adopt smartphones for professional use than bigger farms. Jelinski et al. (2019) [26] found that, among the factors influencing the farmers' adoption of smartphones, the size of herd is positively associated with an increased use. Ramirez (2013) [22] considers the size of farms as a proxy variable of the farms' income. In our case study, the technology adopted is cheaper than other smart farming technologies that may require huge investments by the farmers. As smartphones are a relatively cheap technology, their use is not affected by the income of the farms. At the same time, this result suggests that even smaller farms with smaller herds may benefit from the communication and data management functionalities provided by smartphones. In our case study, gender is not a determining factor in driving the use of smartphones for professional reasons, and this is consistent with the literature [26]. Gender is found as a significant factor in driving the adoption of farming technology in developing countries, where there is a specific familiar organization of the farm's workforce, and women are usually the farm managers [27].

Our study confirms the positive influence of networks in the adoption of technology, and particularly of smartphones, for professional reasons. Especially, our study suggests that in analyzing the influence of the network in disseminating information about technology, not only the existence of the network is important [7–9], but also the type of relationship between the actors. This is a relevant result considering the literature that critically compares multiple networks and invites us to characterize the type of connections among the farmers [17,20,22]. Our results suggest that the

centrality measures of the Production network, and thus the connections among the farmers established for professional help and support, are significant factors in driving the adoption of smartphones for professional reasons. In contrast, the information exchange network does not seem to affect the adoption rate significantly. The actors with more power who are more central in the production network are those more prone to influence a higher use of smartphones for professional reasons. In other words, having an additional professional relationship increases the probability of adopting smartphones for professional usage, more than increasing the information exchange network.

Another important result is connected to the analysis of the network structure. While this study does not regress the network structure's indicators such as density, transitivity, and assortativity to the smartphones usage indicator, the analysis of network structure still provides important insights. The production network seems to be more efficient than the information exchange network in spreading the information about the technology, due to a better connectivity and a lower redundancy of information [9].

The information exchange network brings together farmers that ask for general information and advice about farming activity to other farmers. Usually the central nodes in this network are popular farmers whose opinion is taken into account more frequently by other farmers, independently from the cooperative they belong to. The contacts happen directly in the farms, in formal meetings in the cooperative, or other informal moments. Usually the reputation of those central farmers relies on their experience in the valley, and is connected to their participation in local groups of interest and associations. These farmers are usually the older ones, although our study finds that they are also less prone to use smartphones. This may suggest why the information exchange network is not significant in spreading the information about smartphones.

The production network brings together actors that ask for practical help from other farmers. There is often a reciprocity in the relationships among the actors. It is a more dispersed network, because each farmer connects with a few farmers, which most of the time are neighbors, and for this reason, there is a more distinctive separation in the contacts between the two cooperatives. Some of the farmers with more contacts have also machinery to share, and usually farmers seek advice from other farmers that share similar farming practices and values, so they probably more easily share information about technology.

The diagnosis of networks is important in light of the AKIS approach [3]. The AKIS approach sustains the co-creation of innovation between farmers and other stakeholders. Networks studies are essential to understanding how the information about technology effectively spreads. Results provided by SNA may contribute to design specific actions to spread the knowledge about technology and innovation. Following our results, it is important for policy-makers to investigate the type of network that connects farmers, identifying the one that is more effective and efficient in spreading innovation. This is consistent with the literature about the importance of farmer-to-farmer networks [11,20]. At the same time, SNA provides information about the possible key actors that can be activated in other networks to support the spread and the evolution of innovation.

To conclude, to reduce development disparities between the economic sectors and between the economic centers and the peripheries, smart growth implies a more inclusive development, where innovation and new technologies can play a determinant role in fostering rural development. In this context, the network is both a diagnosis and an action tool. In this study, the network was used as a qualitative and quantitative diagnosis tool. First, we qualified the different connections among farmers in rural areas, and we identified who is central and how; second, we statistically inferred the influence of networks over the adoption of smartphones, compared to other factors. The participation of farmers in networks enhances their capacities to adopt the technologies they use. Nevertheless, not all networks act in the same way: in our case study, professional networks seem to be more efficient than market and information networks.

At the same time, networks are an action tool. Networks enhance the flow of information and the diffusion of social capital. After having used them to diagnose the social structures of farmers,

networks can be used as drivers for the resilience and development of the farming system. This is important in rural marginal areas, where the geographical distance among actors and to services may hamper a widespread diffusion of innovations. Moreover, this function is essential in cooperatives where farmers work together for the same commercial output. In this sense, networks stimulate the share and agreement of common productive strategies, further enhancing the efficiency and the control over the food provision in terms of quality and quantity. In the end, having a better traceability of the products also improves the market position of the cooperative, resulting in higher revenues for farmers.

Further studies could explore the drivers for the creation of specific networks among farmers, as well as what hampers their creation. Moreover, further studies should investigate beyond the farmer-to-farmer connections and analyze more in depth the role of third party stakeholders in influencing the development of networks and the consequent diffusion of innovative knowledge among farmers. When farmers adopt a new technology, networks are essential to generate and disseminate such information, as well as to improve the technology to better respond to farmers' needs.

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