

Public policies for enhancing diffusion of technology: a network analysis for a dairy farmer community in Minas Gerais, Brazil

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ABSTRACT - The objective of this study is to apply Social Network Analysis (SNA) approach to improve the understanding of how to shape effective information diffusion policies among small-scale dairy farmers in rural communities of Brazil, for whom milk production is an important source of income. We interviewed 24 dairy farmers representing all participants of a dairy farmer association in a small-scale production community in the Zona da Mata of Minas Gerais, Brazil. Two sociograms were built by means of an adjacency matrix representing the two internal networks, friendship (F) and advising (A). The beta-centrality and betweenness centrality measures were calculated to identify central farmers and correlate with efficiency indicators in each network (F and A) using a quadratic assignment procedure (QAP). The two internal networks structures and individual thresholds of adoption were represented in an agent-based model (ABM) to simulate the spread of the information among farmers. Our simulations indicate that the assortativity degree of social networks affects the information diffusion among farmers, highlighting the importance of opinion leaders versus convincing a critical mass to implement innovation strategies. Our analysis suggests that vertical policies focused on local opinion leaders will be more effective for enhancing the adoption of techniques that involve investments in private goods such as the adoption of artificial insemination, whereas horizontal policies, such as broadcasting information, will be more effective in encouraging investments in public and semi-public goods, such as the purchase of community cooling tanks and techniques for enhancing milk quality.

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Keywords: dairy cattle, modeling, social behavior, Social Network Analysis

1. Introduction

Total milk production and milk production per cow in Brazil have increased since the early 2000s, but productivity is still low (1,482 L/cow/year) when compared with key milk-producing countries such as the United States (10,610 L/cow/year), New Zealand (4,418 L/cow/year), and the European Union countries (6,775 L/cow/year) (USDA, 2019). This is due, in part, to limited adoption of available technologies, especially by small- and medium-sized farms (Camilo Neto et al., 2012; Fassio et al., 2006). Public policies and private strategies focused on enhancing the diffusion of innovations among Brazilian

farmers (including dairy farmers) could increase agricultural productivity and reduce inequalities such as lower incomes for smaller producers (Belik, 2015). Many rural extension agencies in Brazil employ the two-step-flow strategy (Watts and Dodds, 2007) using opinion leaders and “Demonstration Units” to propagate new techniques or practices in small dairy farmer communities (Moraes et al., 2015; Simões et al., 2015). However, to the best of our knowledge, none of them has considered the structure of the underlying social network of dairy farmers to inform that policy.

Social network analysis (SNA) is a method for investigating social structures. It has been applied to many fields, e.g., rural sociology and agriculture, studies of poverty and violence, sociology of education, religion, and military and political interactions (Otte and Rousseau, 2002). Social network analysis represents networks with two basic elements, nodes and ties (or linkages), which are visualized in sociograms as points and lines, respectively. The nodes in a network are expected to be active agents such as individual persons. Nodes can also be groups of individuals, such as teams, firms, cities, countries, or whole species. In this study, we treat each dairy farmer as a node in a rural social system. Ties in a network represent the relationships between two or more nodes and can also be characterized by a multitude of types, e.g., two individuals being married or co-owners of a business (Borgatti et al., 2013; Christakis and Fowler, 2009). We assume in this study that dairy farmers are the nodes and the ties comprise friendship or sharing of information about agricultural technologies.

Consideration of social networks is relevant because diffusion of new technologies and social practices is a social process that involves interpersonal communication and relationships. This implies that information about the social network is vital for understanding how to enhance the adoption of an innovation in a system (Rogers, 2003). For example, if information is not reaching many or a key subset of farmers, this suggests the need to increase awareness by adopting a broad-based, “broadcast” dissemination campaign. In contrast, if information is spreading but farmers’ decision to adopt is heavily tied to peers’ decisions and adoption does not occur, an effort to encourage adoption among well-positioned (central) farmers would be suggested. Despite the vast body of network-based research on these issues in real settings – including rural communities (Richter, 2019; Rockenbach and Sakdapolrak, 2017) –, as far as we know, there are no studies for diffusion of technologies among dairy farmers that couple the topology of the social networks in which farmers are embedded, the communication strategies they adopt, and their intrinsic perception of the technology attributes in a single framework (Thirunavukkarasu and Narmatha, 2016).

Thus, the objective of this study is to apply the SNA approach to improve the understanding of how to shape effective diffusion policies among small-scale dairy farmers.

2. Material and Methods

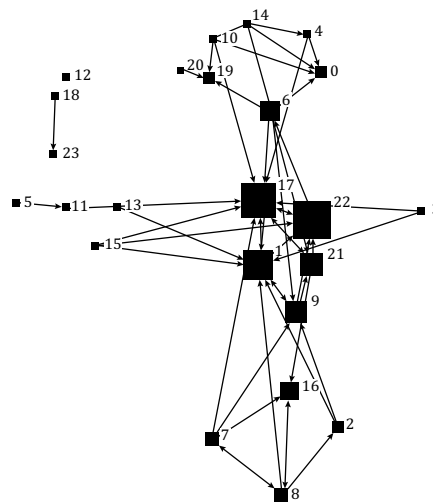
Twenty-four dairy farmers located in a small community in the municipality of Viçosa, Minas Gerais, Southeastern Brazil (20°42'37" S, 42°54'21" W), were interviewed by means of a semi-structured questionnaire that included questions about technological and social attributes. For the purpose of the SNA, we treated the 24 farmers as representing the relevant object of study, the internal network of the community defined as the Associação de Agricultores Familiares do Córrego São João, in Viçosa. A small number of participants in a network is a common characteristic of rural communities like ours and a common feature of SNA studies. For instance, the rural communities studied by Nyantakyi-Frimpong et al. (2019) range from 16 to 29 farmers and those studied by Pigatto et al. (2020) have 12 Brazilian fish farmers.

The questionnaire included a “roster” instrument, in which farmers were asked to answer two questions from a list of names (Butts, 2008): “Who of your neighbors do you meet often in social occasions?” and “From whom do you get technical advice or information about new production practices?” This information forms the basis for two sociograms, displaying the friendship (F) and the advice (A) social networks, respectively (Figure 1). The sociograms were built using Ucinet and NetDraw softwares by means of an adjacency matrix. In our case, a squared matrix with rows and columns labeled 1,2,...,g in identical order represents all farmers in the network. The entries in the matrix, x_{ij} , record which pair of

farmers are connected (also named as adjacent or neighbors). The value 1 is set for the (i,j) th cell (row i , column j) if there is a connection between n_i and n_j and 0 otherwise. In other words, if farmers n_i and n_j are connected, then $x_{ij} = 1$, and if farmers n_i and n_j are not connected, then $x_{ij} = 0$ (Wasserman and Faust, 1994). From the adjacency matrix, we calculate two centrality measures to identify the central farmers within the network, the Bonacich's centrality also known as beta-centrality (Bonacich, 1987) and betweenness. Beta-centrality is used for quantifying social status in networks and implies that a focal farmer's status is a positive function of the number of connections of their friends (Podolny, 2005). The betweenness measures how much a farmer is positioned between two other farmers or connects two groups of farmers (Freeman, 1977). The correlations between the centrality measures and efficiency indicators (average daily production, cow yield, and herd size) with each network (A and F) were calculated, and a t test following the quadratic assignment procedure (QAP) using the Ucinet was performed to identify group differences by technology adoption status (adopt or not adopt) in the two networks. We divided farmers into two groups based on their use of artificial insemination (AI), assuming that those who use AI are also more likely to be innovative and adopters of other technologies such as nutrition, management, and sanitary practices.

The QAP is a matrix permutation procedure used to perform t tests and calculate the significance level (P-value) of selected variables. This technique is recommended when the variables do not follow a

a) Friendship network - F



b) Advice network - A

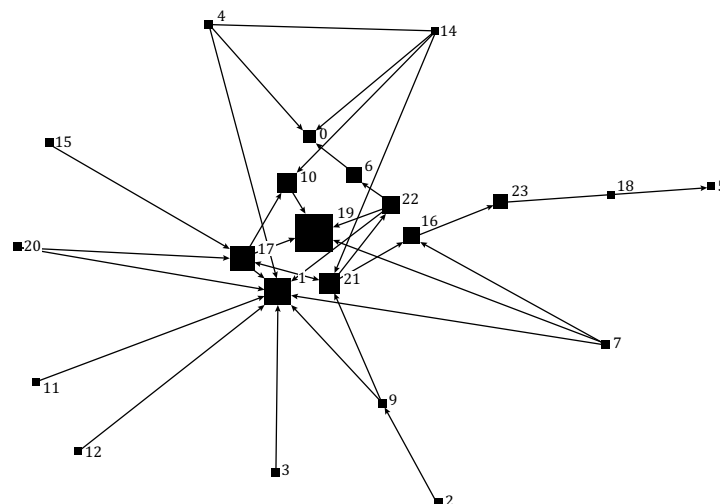


Figure 1 - Friendship network - F (a) and Advice network - A (b) of dairy farmers of the Associação de Agricultores Familiares do Córrego São João in Viçosa, MG, Brasil.

normal distribution, and independence and random samplings are not expected. These features are typical of network variables; for instance, centrality measures such as beta-centrality show a power-law distribution and the actor's behavior is always dependent on its adjacent (connected) actors (Borgatti et al., 2013). The algorithm proceeds in two steps. In the first step, it computes Pearson's correlation coefficient between corresponding cells of the two data matrices. In the second step, it randomly permutes rows and columns and re-computes the correlation and other measures. The second step is carried out hundreds of times to compute the proportion of times that a random measure is larger than or equal to the observed measure calculated in step 1 (Borgatti et al., 2013). We assumed the proportion of <10% (P-value) to suggest a strong relationship between the matrices that is unlikely to have occurred by chance.

Two questions are of special interest for this study. First, in which network (A or F) is it easier to promote the dissemination of a better practice or technology? And secondly, what policies should we use to reach that goal? To answer the questions, an agent-based model was developed in which the decision to take up a new behavior, e.g., adopting a more advanced technique such as AI, is determined by the proportion of friends who have already adopted this behavior. More formally, it was assumed that a farmer can be in one of two states: adopting or not adopting a new technique.

The model is based on the theoretical approach proposed by Valente (1996) and revisited by Easley and Kleinberg (2012). The simulation starts by setting the farmer initially as non-adopter, apart from the 10% of higher Bonacich's beta-centrality. The model then evolves through a series of discrete steps, and the algorithm follows the logic: suppose that a fraction p of the neighbors of agent i has the behavior A (adopt), and a fraction $(1 - p)$ has the behavior R (reject). If i has d neighbors, then $p \times d$ adopt A and $(1 - p) \times d$ adopt R . Thus, if i chooses A , it evaluates the information as $p \times d \times a_i$, and if i chooses R , it evaluates the information as $(1 - p) \times d \times r_i$, so A will be the best choice for i if $p \times d \times a_i > (1 - p) \times d \times r_i$. By rearranging the terms, it has: $p > r_i / (a_i + r_i)$, that is, i will only adopt an innovation if the fraction of neighbors who previously adopt p is greater than its threshold value generated by the evaluation of the benefit of the information.

The individual adoption thresholds were obtained directly from the questionnaires. If a farmer has answered that she/he adopts a new practice only if most of their friends do the same, he/she would be set to a high threshold value of 0.5. If the answer is that he/she adopts a new practice only if some of their friends do it, the intermediate value of 0.33 is established, and, finally, a low threshold of 0.25 is set if she/he assumes to be one of the first to adopt it among the neighbors. These threshold values were set by the authors and adjusted to differentiate the farmers' adopting behavior when implemented in the simulation model.

The ABM algorithm simulates a number of discrete steps, which represent farmer decision points and not a specific time interval. This is a characteristic of simulation models that operate with discrete steps and not on continuous-time (North and Macal, 2007). For each step, the model assumes that every farmer re-assesses their decision (to adopt or not) based on the fraction of neighbors adopting and their threshold level as described in the algorithm. A larger number of steps the algorithm needs to diffuse a certain technology (information) through the network implies a longer chronological time for adoption. The software AnyLogic (Personal Learning Edition) was used to incorporate the networks A and F and implement the algorithm.

3. Results

3.1. Descriptive results

On average, the farmers were 57 years old and had 20 years of experience in dairy farming. Nearly four-fifths (79%) had four years or less of formal education. The majority (67%) lived on the farm and had milk as the main source of income of their family (62%). The average farm area was 24 ha, and the daily milk yield was 146 L, with an average of 9.9 L/cow/day. The use of available

technologies to enhance milk production was limited: only 16% of farmers used AI, 18% early weaning, and most of them (54%) milk only once per day. These data are consistent with the reality of a large number of producers in Brazil and indicate that the adoption of appropriate technologies may result in economic benefits for farmers and consumers (Gomes, 2006; Melo and Reis, 2007; Simões et al., 2019).

Figures 1a and 1b represent the friendship and advising networks, respectively. Each node represents a farmer and each line represents the existence of a relationship (connection) between two farmers. Node size is given by farmers' social status, quantified by their Bonacich's centrality. Hence, farmer 19 in A has a high beta-centrality score because she/he is connected to a larger number of other farmers who are highly connected amongst themselves. Thus, central farmers in F, such as farmers 1 and 22, have higher betweenness centrality scores because they connect two otherwise disconnected clusters of farmers at the top and at the bottom of the sociogram. Betweenness centrality is important for the diffusion of new ideas, because it measures how much potential control a farmer has over the flow of information. For instance, conservative farmers who have high centrality scores can choose to withhold or distort information she or he receives (Nyantakyi-Frimpong et al., 2019).

The two networks have different topologies and assortativity degrees. Friendship (F) displays positive assortativity, which implies that high-status farmers prefer to connect to other high-status farmers and low-status farmers connect to other low-status farmers. Advice (A) presents the star-shaped structure created by negative assortativity (or disassortativity), which occurs when high-status farmers prefer to connect to low-status farmers, and vice-versa. Positive assortativity is normally driven by homophily processes and disassortativity by complementary needs (Newman, 2002). Thus, A displays disassortativity because less influential farmers look for information among more influential and presumably more informed ones, and F presents positive assortativity because people tend to select friends among similar persons.

The pairwise correlations among factors (betweenness centrality, average daily production, cow yield, and herd size) explain the social status in each network (Table 1). Once non-statistically significant factors have been discarded, we can conclude that the most important issue in determining influence in F is where people are placed in the network. Influence here stems mostly from farmer's betweenness centrality that came from her/his ability to connect people. In A, on the other hand, influence seems to come mainly from innovativeness, which appears to stem from the fact that an actor tends to adopt new practices and technologies earlier, which explains her/his productivity. This result can be confirmed by showing that farmers of higher status tend to be the most innovative (for instance, using techniques such as AI) in the A network but not in the F network (Table 2). The average beta-centrality score (normalized) of the adopter is 1.21 in A and 0.70 in F.

3.2. Simulation results

The predicted spread of a new technology among the studied farmers was obtained by simulating the model for F and A networks (Figure 2). Starting the diffusion by the higher-status individuals works better in A, to the extent that the new technology will spread faster and reach a large number of

Table 1 - Pairwise correlations and significance levels among factors that determine social status in the friendship and technological networks

	Farmers' beta-centrality score	
	Friendship network (F)	Advice network (A)
Betweenness centrality	0.866(<0.001)	0.358(0.086)
Average daily production	-0.026(0.905)	0.370(0.075)
Cow productivity	0.354(0.090)	0.716(<0.001)
Herd size	-0.011(0.953)	0.359(0.086)

individuals. Furthermore, this strategy is likely to be relatively easy to implement, since higher-status individuals in A are the most innovative as well, which means that they will be more susceptible to be persuaded in adopting new behaviors than the more influential farmers in F.

Therefore, if the objective is to disseminate new technologies or production practices, the vertical strategy of seeding the network by making a new technique available to more-influential individuals should be preferred to horizontal strategies such as mass communication campaigns (Wakefield et al., 2010). This is because advice networks tend to display the star shape typical of disassortatively mixed systems, since individuals tend to identify people who are experts and credible sources of information and who have considerable technical knowledge. However, diffusion of new technologies often requires behavioral changes that involve trust, mutual understanding, and interpersonal affect, which disseminate mostly through networks like F (Valente, 2012).

Thus, it would be worth addressing whether there are effective means to enhance the diffusion of the required social behaviors in networks like F. Comparing the informed fraction (Figures 3a, 3b, and 3c), one can note that one possible way to do so is by changing some individual attributes such as the predisposition to adopt innovations, which could be done by implementing horizontal policies seeking to increase farmers' awareness of the benefits potentially brought by the new technologies, which would decrease the individual adoption thresholds. This means that if we seek to design and implement effective communication campaigns for spreading new technologies or behaviors, we should focus on more-influential individuals. In assortative/homophilic networks like F, however, we should first attempt to change individual attributes by means of horizontal measures such as educational campaigns.

Table 2 - T test of beta-centrality means by artificial insemination (AI) groups

	Group	Obs.	Mean	SD	P-value*
Friendship network (F)	Non-adopters of AI	20	0.553a	0.765	0.7807
	Adopters of AI	4	0.706a	1.023	
Advice network (A)	Non-adopters of AI	20	0.443a	0.612	0.0648
	Adopters of AI	4	1.211b	1.296	

SD - standard deviation.

* P-value = significance level obtained by using a permutation test.

a,b - Different letters mean statistically different results ($P < 0.10$).

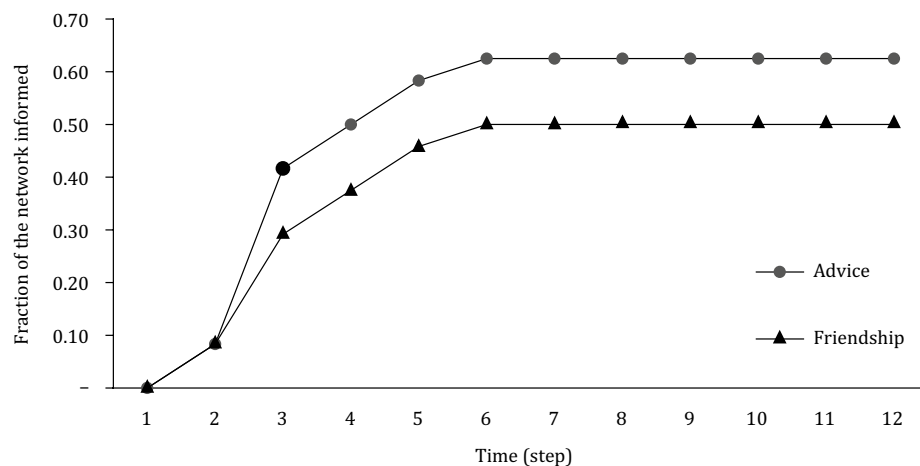


Figure 2 - Simulated diffusion of a new technology among dairy farmers of the Associação de Agricultores Familiares do Córrego São João based on A and F networks.

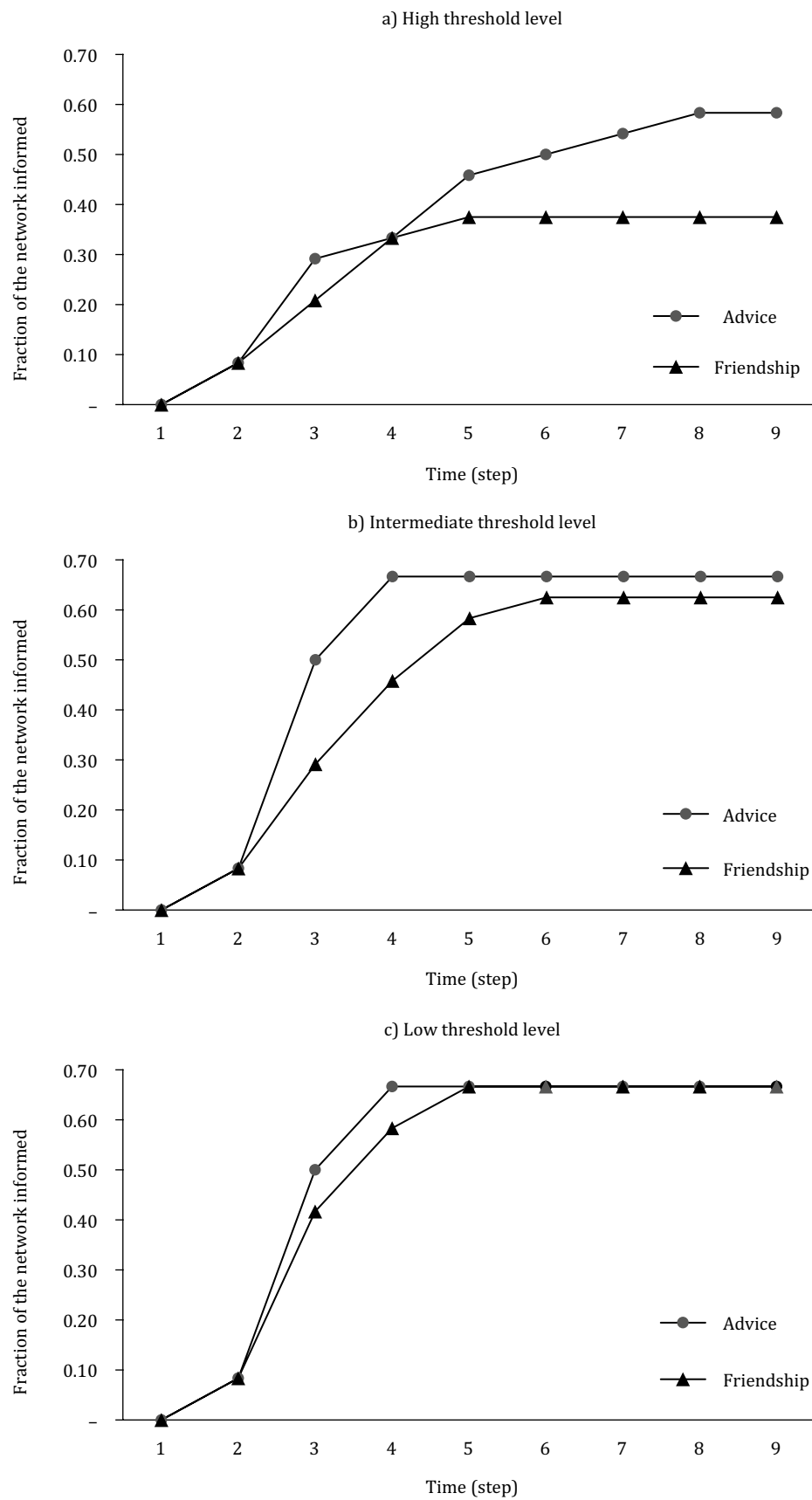


Figure 3 - Simulation of information diffusion in the two networks (A and F) using the opinion leader communication strategy and different threshold levels.

4. Discussion

The spread of new behaviors through a social network could be enhanced by a two-step flow process, according to which opinion leaders in social network would act as intermediaries between mass media (or public agencies) and ordinary people in the dissemination of new ideas and behaviors (Watts and Dodds, 2007). We showed that this can be true but not in all types of networks. Depending on the value of the adoption threshold, people in friendship networks, where social ties are mostly based on homophily, can be highly resistant to behavior change. The implication of this property of F-like systems is that they will be assortatively mixed, i.e., they will display a preference for high-status people to attach to other high-status ones (Newman, 2003). A-like systems, on the other hand, tend to display a disassortative mixing pattern, that is, low-status people are more likely to attach to high-status ones (Jackson, 2008). This outcome has been confirmed in applied studies for small and medium rural communities around irrigation perimeters (Bueno, 2015) and in the present study.

The network topology has important implications for the diffusion of new behaviors and technologies. For instance, a major finding of recent diffusion research is that whatever is flowing through a social network—diseases, information, or behaviors—will spread faster and by a greater number of people in A-like systems than in F-like systems (Morris, 2003; Rogers, 2003). It has been reported, for example, that sexually transmitted diseases (STD) rates are higher among blacks than whites in the United States because of differences in the sexual network patterns of the two groups. The explanation is that blacks with many partners have sex with other blacks with many and few partners (as in A), while whites with many partners tend to have sex with other whites with many partners, and whites with few partners tend to have sex with whites with few partners (as in F). This keeps STD in the core of active white partners (Christakis and Fowler, 2009).

To better understand this result, in A-like systems, a large number of farmers are located in the periphery of the network, who can be influenced by a single adopter friend (see, for instance farmers 3, 12, and 12 - Figure 1b). In F-like systems, on the contrary, even the most peripheral individuals, at the top and at the bottom of the sociogram, hold relationships with a relatively large number of people and, hence, are possibly influenced only by a larger number of friends (see, for instance farmers 14 and 8 - Figure 1a). This means that, for an innovation to be disseminated through F-like networks in the sense of reaching a large part of the population, it is necessary to encourage adoption by a relatively large critical mass of early adopters that, once persuaded to adopt it, trigger a disproportionately large change in the opinion of the whole population. We have shown that one way to do so is by promoting policies that decrease individual thresholds of adoption, for instance, by increasing the awareness of the benefits of the new technologies among uninformed farmers.

An important implication of this outcome is that different policies are recommended for speeding diffusion of different types of practices or technologies in systems. Because it stimulates the adoption of technologies embedded in pure private goods, such as investments in equipment and material for using the AI technology, the relevant underlying social network is probably similar to A. In such case, we predict that vertical policies focused on opinion leaders might suffice as they influence the average farmers to adopt it. However, for the diffusion of public or semi-public goods, i.e., non-totally rival and only partially excludable ones such as community cooling tanks and milk quality pooling techniques, the relevant underlying social network will likely be more similar to F. In this case, farmers have to trust each other to immobilize capital, which means that investments will be profitable only if a large part of the population agrees to contribute. Thus, we predict that horizontal policies aiming at creating a critical mass of adopters willing to cooperate with each other in the funding of the new technology might be more effective to speed diffusion.

Although more studies are needed to evaluate and allow generalization of these predictions, the literature on technology diffusion and adoption in rural social systems suggests that they might apply to other settings as well. For instance, the adoption of financial innovations, such as the decisions to purchase weather insurance by rice-farming households in China and the participation in microfinance

programs in India, were not associated with the decisions of the participant's social contacts. Instead, they were greater when the first person to be informed of the programs was more central than others in the underlying networks, which we suggested is more likely to occur in A-type networks (Cai et al., 2015; Banerjee et al., 2013). The provision of public goods such as investments in the maintenance of irrigation systems and the purchase of new vessels in small in-shore fisheries, otherwise, seems to depend more on the fact that individuals are well known to each other and are connected to one another in multiple ways as in F (Ostrom, 2009). In such settings, the adoption of more efficient economic behavior and technologies depends crucially on the building of a prior common understanding that the expected benefits from an innovation will exceed the immediate and long-term expected costs. In this paper's parlance, that means that to persuade dairy farmers to adopt new techniques or practices, public agencies should focus first on broadcasting information through the underlying social networks to lower their adoption threshold.

5. Conclusions

The present study suggests a new way to choose policies to speed diffusion of innovations in typical dairy systems and rural communities in Brazil and other low- and middle-income countries. The use of social network analysis can help policymakers to identify central and most influential farmers in the community and facilitate to recognize the network topology. Specifically, we offer two main findings on the subject employing a dynamic simulation model. First, the diffusion of new practices in dairy systems or investments in private goods, such as artificial insemination, is more likely to occur if the first people to adopt them are central to the network of the community. For the provision of public and semi-public goods, such as the purchase of community cooling tanks and techniques for enhancing the milk quality, we recommend the adoption of a two-step dissemination strategy, in which broad-based educational campaigns are adopted before innovation is made available to opinion leaders.

Conflict of Interest

The authors declare no conflict of interest

Author Contributions

Conceptualization: A.R.P. Simões and N.P. Bueno. Data curation: F.M.S. Almeida. Formal analysis: A.R.P. Simões and N.P. Bueno. Investigation: A.R.P. Simões and N.P. Bueno. Methodology: A.R.P. Simões, N.P. Bueno and F.M.S. Almeida. Resources: F.P. Leonel. Validation: J.D. Reis. Visualization: F.M.S. Almeida and J.D. Reis. Writing-original draft: A.R.P. Simões, N.P. Bueno, C.F. Nicholson, J.D. Reis and F.P. Leonel. Writing-review & editing: A.R.P. Simões, N.P. Bueno, C.F. Nicholson, J.D. Reis and F.P. Leonel.

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