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Research Articles

Social network factors affecting adoption of Mobile app by farmers

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ABSTRACT

Effect of social network on adoption of Mobile app was studied in Nashik and Sangli districts of Maharashtra, India by interviewing 800 grape growers during 2016–17. Individual characteristics like income, landholding, caste, area under grapes and number of smartphones were significant factors determining the adoption of mobile app. In social network factors, village adoption rate, membership, education, landholding and frequency of communication were significant determinants of adoption. Village adoption rate of the technology resembles network behavior. Therefore, both social network characteristics and social network behavior influences the adoption decision of farmers. It shows that adoption is not just mimicking by the farmers, but it is a social learning process. The results emanating from the study provide insights to extension agents to devise strategy for introduction of any technology/ICT in agriculture. The way out to implement the strategy is to use extension methods that focus on social learning like Farmers Field Schools*;* target the farmers having more education, landholdings and who frequently interact with the large number of farmers to facilitate and enhance the adoption of new technology/ICT.

Keywords: Adoption, Mobile app, Social network characteristics, Social network behavior

It is well known that farmers' decisions to adopt particular innovation are not only a function of the head of the household alone but it occurs in broader social settings through the social network of the farmers (Doss 2006, Ramirez 2013). A social network is defined by individual members (nodes) and the links among them through which information, money, goods or services flow (Maertens and Barrett 2011). Networks essentially function as the exchange of information between individuals who share social and informational resources (Carlsson and Stankiewicz 1991). Analysis of the social network of farmers helps in understanding the patterns and processes involved in diffusion and adoption of innovations by the farmers in their social ecosystem. The literature shows that factor, viz. age, education, landholding, membership, perceived benefit of technology, cost reduction etc. had contributed to adoption of technology by farmers. Very little work is done on the effect of social networks on farmer's adoption.

Some studies deciphered the effect of social networks on the adoption behaviour of the farmers (Matuschke and Matin 2009, Conley and Udry 2010). Participation in organization by farmers affects adoption of technology by the farmers (Ramirez 2013). Social network of farmers enhances the social learning and adoption of the technology (Case 1992, Magnan *et al*. 2013). Knowing and understanding more complex technologies required strong external ties and flows of the same information from multiple sources (Todo *et al*. 2015). Some studies also showed more effect of the social network when the number of adopters was small in the network (Bandiera and Rasul 2006). However, some studies found that "clustered" networks, in which an individual's friends were generally also friends with each other, facilitate individual adoption of health behaviours to a greater extent than "small-world" networks (Centola 2010). Rogers (1995) argued that ties to peers were more important in changing behaviour and actual adoption of innovation, but Granovetter (1973) found that for search for a job, people relied more on weak ties than on strong ties. Thus, with various dimensions and intensity, social networks have influence over the adoption of technologies by the farmers. Therefore, present study attempts to study the characteristics of individual farmers and their social networks that influence the adoption behavior of farmers.

MATERIALS AND METHODS

Locale of study and sampling: Present study was carried out in Nashik and Sangli districts of Maharashtra as these districts account for most numbers of users of mobile app as well as largest producer of grapes. The mobile app having complete information, decision support system and forecasting of weather, pests and diseases to the grape growers was developed during 2012 by ICAR-National

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Research Institute for Grapes, Pune and Maharashtra, commercialized by the S K Crop tech company from Maharashtra. A multistage sampling procedure was followed for selecting respondents. From each district, 350 grape growers who were using the app were selected randomly. To make the comparison, 100 non-adopters of the app were selected from both the districts.

Data collection and analysis: Data about personal, socio economic variables of farmers and their social networks were collected using personal interviews of the farmers during 2016–17. Farmers were asked to name three important persons to whom they generally ask information related to agriculture. In addition to this, data of network persons, viz. education, landholding, association in village organization, distance from the farmers, frequency of interaction etc. were also collected. For analysis of the social network characteristics of adopters and non-adopters, the method followed by Matuschke and Matin (2009) was used. Logistic regression model was used for determining factors affecting adoption of Mobile app. Using dummy variable 1 for the adopter and 0 for the non-adopters we fit the® logit model as

$$Y_i = \alpha + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_i$$

where, Y is adoption quotient; α is an intercept; β_i is regression coefficients, ε_i as error term and X_i are independent variables. We included variables like age, education, farming experience, cast, land holding, farming experience, area under grapes, annual income and number of smartphones in household under the individual characteristics of farmers and variables like village adoption rate, SNM Education (SNM -Social Network Member), SNM Cast, SNM Landholding, SNM Distance, SNM Communication and SNM Association under the social characteristics. Based on above variables, the empirical model was specified and estimated to predict the likelihood of probability of factors influencing the adoption of mobile app by the farmers, as follows;

$\text{Log}\lambda_i = \alpha + \beta_1 \text{age} + \beta_2 \text{eduction} + \beta_3 \text{familysize} + + \beta_4 \text{landholding} + \beta_5 \text{cast} + \beta_6 \text{Farmingexperience} + \beta_7 \text{areagrapes} + \beta_8 \text{Income} + \beta_9 \text{smartphone} + \beta_{10} \text{villageadoption} + \beta_{11} \text{SNM education} + \beta_{12} \text{SNM cast} + \beta_{13} \text{SNMlandholding} + \beta_{14} \text{SNM distance} + \beta_{15} \text{SNM communication} + \beta_{16} \text{SNM association} + \varepsilon_i$

It was assumed that the education of farmers, family size, landholding, caste, annual income, and number of smartphones in households will be positively related to the adoption of mobile app, while age, farming experience and area under grapes will be negatively related to the adoption of mobile app. In network characteristics, it was assumed that all variables except caste and distance will have a positive influence on adoption of mobile app.

The cumulative logistic probability function for the logit model is specified as;

$$P = F(Z) = \frac{1}{(1 + e^{-(\alpha + \beta i Xi)})}$$

where Z, set of explanatory variables X; F(Z), cumulative logistic function; e, base of natural logarithms and P, probability of success when explanatory variable has the value X.

Logit models are interpreted using Odds and Odds ratios where odds ratio indicates the multiplicative impact in the odds for a unitary change in the explanatory variable when other variables are constant. Exponentiated coefficient greater than unity, indicates that the odds are increasing, and negative value indicates that the odds decrease. Deviation of the exponentiated coefficient value from unity indicates the magnitude of impact on the odds for a unit change in independent variable. A marginal effect is an informative means for summarizing how change in an adoption of app is related to change in a covariate. These are the marginal effects when all other variables equal their means. Marginal effect of X on the probability of making choice 1, evaluated at mean of X is estimated as;

$$\frac{\partial E(y_i \mid \bar{x})}{\partial x_k} = \frac{\partial g(\bar{x}, \hat{\beta})}{\partial x_k} \qquad k=11,...,K$$

where y, choice variable, *x*, vector of explanatory variable; β, vector of parameter estimates; x_k, k^{th} component of x.

To find out the important dimensions of the social network of adopters influencing adoption of the mobile app, Principal component analysis using Varimax rotation method was used.

RESULTS AND DISCUSSION

Individual and social network characteristics of adopter and non-adopters: The personal and social economic characteristics of adopters and non-adopter shows that (Table 1) there was a significant difference between education level and landholding of the adopters and non-adopters where adopters had more education and landholding than non-adopter of the mobile app. Annual household income of the adopters was significantly higher than the non-adopters of the mobile app. The adopter had more mobile phones (smart phones) in their household than non-adopter. Adopters had less percentages of area under grapes as compared to non-adopters.

Village adoption rate in case of adopters was higher (6.67%) than non-adopters, indicating influence of social network and social learning on adoption of mobile app. Average education and land holding of the social network members of adopters was more than their counterparts. Share of network members from their same caste was more in non-adopters (87%) than adopters. Distance between social network members and adopters were more (3.62 km) than the non-adopters, indicating more outreach of adopters than non-adopters. Communication in terms of frequency of interaction per month was more in case of social network members of adopters (7.63) than non-adopters. More percentages of social network members (47.87%) of adopters were associated with the village institutions than that of non-adopters (41.30%).

Factors affecting adoption of mobile app: Age showed

Table 1 Individual and network characteristics of adopter and non-adopters

Variable	Description	Adopter	Non-adopter	P value*
Individual characteristics				
Age	Farmers age in years	40.94	43.56	0.013
Family size	Number of persons in household	06.44	06.29	0.554
Education	Years of formal education of farmers	13.09	11.84	0.000
Landholding	Land holding of farmers in acre	03.52	02.94	0.016
Cast	Social category of farmers (General =1, otherwise=0)	82.70	89.10	0.246
Farming experience	Years of experience in grape cultivation	14.37	15.20	0.247
Area under grapes	Share of area under grapes in total area of farmers	61.81	68.75	0.030
Income	Annual household income of the farmers in Lakh Rupees	14.47	10.56	0.003
Smartphone	Number of smartphones in household	01.82	01.52	0.001
Social network characteristics				
Village adoption	Share of farmers who have adopted the mobile app from respondents village	06.67	02.70	0.000
SNM education	Average education of network members (Formal education)	13.53	12.40	0.000
SNM cast	Share of network members who have same caste as the individual farmers	80.01	87.00	0.245
SNM landholding	Average landholdings of network members (In acres)	09.11	06.44	0.002
SNM distance	Average geographic distance to the network members (Km)	03.62	02.88	0.563
SNM communication	Average frequency of communication (per month)	07.63	06.85	0.023
SNM association	Share of network members that are members in village association	47.87	41.30	0.388

*P value using t-test

a positive but non-significant relationship with the adoption of mobile app (Table 2). Negative relation was expected as younger farmers were more ready to adopt new technology as found by Ali (2011) and Das (2014). Mittal and Mehar (2015) also found positive but non-significant relation with the age in adoption of ICT. Family size of the farmers negatively though non-significantly affected the adoption of mobile app. Education was positively related to the adoption of mobile app. Many empirical studies have shown positive influence of education on adoption of technology by the farmers (Das 2014, Mittal and Mehar 2015). With one percent increase in education level, probability of adoption of mobile app increased only by 0.3%. Ali (2011) while studying adoption of ICT in vegetable farmers also found a non-significant positive relation of education with the adoption of mass media information by the farmers.

Decrease in size of landholding by one percent, resulted in increased probability of adoption of mobile app by 1.3%. Ali (2011) found similar findings in his study of vegetable growers where comparatively smaller landholdings were more likely to use media information than large farmers. Farmers from the general social category were more likely to adopt the mobile app than other cast members. With one percent increase in general caste farmers, probability of adoption of mobile app increases by 6.4%. Similar observations were also recorded by other studies (Das 2014). Farmers with less farming experience were more likely to adopt the mobile app than more experienced

Table 2 Factors affecting adoption of Mobile app

Explanatory variable	Logit coefficient		Marginal effects	
	Coef.	z-value	Dy/dx	z-value
Individual characteristics				
Age	0.013	0.53	0.001	0.53
Family size	-0.104	-0.98	-0.004	-0.98
Education	0.083	1.07	0.003	1.08
Landholding	-0.350**	-2.4	-0.013**	-2.46
Cast	1.680**	2.4	0.064**	2.45
Farming experience	-0.065*	-1.74	-0.002*	-1.74
Area under grapes	-0.027***	-2.95	-0.001***	-3.05
Income	0.114***	3.34	0.004***	3.44
Smartphone	0.738*	1.94	0.028*	1.96
Network characteristics				
Village adoption	0.960***	6.55	0.037***	7.62
SNM cast	-0.009	-1.47	-0.001	-1.48
SNM education	0.227***	2.61	0.008***	2.69
SNM landholding	0.243***	3.33	0.009***	3.45
SNM distance	0.131	1.59	0.005	1.60
SNM communication	0.298**	2.29	0.011**	2.31
SNM association	0.003	0.75	0.001	0.75

(LR chi2(16) = 154.20; Prob > chi2 = 0.0000; Pseudo R2 = 0.4474; Log likelihood = -95.2288). ***P≤ .01; **P≤ .05; *P≤ .1.

farmers. Negative relationships were expected, as less experienced farmers would seek more information from different sources. Farmers having less percent of area under grapes were more likely to adopt the mobile app, maybe because of best management practices they used on a small scale than on large areas. The findings are well supported by the study of Ali (2011). Farmers having more number of smartphones in household were more likely to adopt the mobile app as compared to farmers with only one smart mobile in household. With one percent increase in smartphones, probability of adoption of mobile app would increase by 2.8%.

Among social network characteristics, village adoption rate significantly and positively affected the adoption of mobile app. With one percent change in the village adoption rate, probability of adoption of mobile app increases by 3.65%. Village adoption rate as a variable shows the impact of social network and social learning on the adoption of the mobile app. Matuschke and Matin (2009) used village adoption rate as a proxy variable for social network effect and found that share of adopting network members (proxy for village adoption) was significantly influencing the adoption. Other network characteristics were not influencing adoption significantly. They concluded that network behavior was more important for adoption than the network characteristics. In present case education, landholding and communication of social networks were significantly related with the adoption, contrasting with the above theory and confirming that both social network behavior and social network characteristics were important in adoption of mobile app. Education of the social network members was a highly significant determinant of adoption of mobile app. One unit change in education will likely to enhance the probability of adoption of mobile app by 0.8 unit. Landholding of the social network was a significant factor affecting the adoption of the mobile app. With one unit change in the landholding of social network members, probability of adoption of mobile app increases by 0.9 units. Probability of adoption of mobile app increases by 1.13% with one percent increase in the frequency of interaction with the network members. These findings are in concordance with Bandiera and Rasul (2006), who found that network effect is stronger for farmers who report discussing agriculture with others.

There was a positive influence of social network member distance from farmers and adoption of mobile app. Other studies have shown that less the distance of social members, more would be influenced on adoption of the technology (Ward and Pede 2014, Muange and Schwarze 2014). Near distance has an advantage in terms of more frequent exchange of information while long distance can be more diverse and can give new information to the farmers. Todo *et al*. (2015) argued that knowing and understanding technologies that are more complex require strong external ties and flows of the same information from multiple sources. In this context, the positive effect of long distance social network members can be explained. There was a negative and non-significant relationship between share of network members from the same caste and adoption of the mobile app. It indicates that for technology like mobile app, adopters searched for information from individuals who were not necessary from the same caste as them. Share of network members that are members in village association was positively and non-significantly influenced by the adoption of mobile app by the farmers.

Important dimensions of social networking of adopters: There are direct and indirect forces that influence the mechanism of social networks in adoption of technology (Table 3). To overcome the overlapping influence of variables and bringing parsimony in a set of variables, the Principal Component method was applied. Principal axis factor analysis with Varimax rotation was conducted to assess the underlying structure for the variables related to the network characteristics of the adopter of mobile app. Based on Eigen values, three factors were found. After rotation, the first factor accounted for 27.43%, the second factor 19.29%, and the third factor for 18.08% of total variance. Cumulatively these three dimensions could explain 64.8% variance in the data set.

These three factors seem to index three important dimensions of the social network members of the adopters, viz. individual characteristics, social characteristics and ease of interaction. The first factor, which indexed individual characteristics, had strong loadings on the education, landholding of the network members and distance from network members. The second factor, which indexed social characteristics of the network members, had high loadings on caste and association of social network members in the village association. The third factor, indexing ease of interaction loaded highly on the frequency of interaction with the social network. Therefore, to identify the person for transfer of technology in a village, one should ensure and select somebody with a high level of individual characteristics like education, land holding etc. so that

Table 3 Important dimensions of social networking using Principal component method

Variables	Factor loading			Communality (h^2)
	I-Individual characteristics	II-Social characteristics	III-Ease of interaction	
Education	0.692	-0.076	0.077	0.491
Landholding	0.794	-0.077	0.210	0.681
Distance	0.726	0.069	-0.342	0.650
Cast	-0.073	0.764	-0.184	0.624
Association	-0.009	0.746	0.226	0.607
Communication	0.057	0.035	0.912	0.837
Eigen values	01.64	01.15	01.08	
% of variance	27.43	19.29	18.08	

Kaiser-Meyer-Olkin Measure of Sampling Adequacy=0.555; Approximate Chi-square=271.63; Bartlett's test of Sphericity is significant at 5 % level of significance.

there are more chances of farmers to include them in their social network and interact for adoption of new technology.

Marginal effect shows that variables like village adoption rate of technology, frequency of communication, education and landholding of the social network members has more influence on enhancing the probability of adoption of the mobile app. Principal component analysis discerns the important dimensions of the social network members of adopters, viz. individual characteristics, social characteristics and ease of interaction. The findings have implications for the extension agency interested in the introduction of any technology/ICT in agriculture. Village adoption rate of the technology resembles network behavior, which extension agents should understand before introduction of any technology in the village. It shows that adoption involves not just mimicking by the farmers, but it is a social learning process. Therefore, extension methods that focus on social learning like Farmers Field School, field visit, result demonstration*s* etc. should be used to facilitate the social learning process and adoption process. Along with network behavior, network characteristics were found to be important determinants of the adoption; farmers having more education, landholdings and interacting frequently with the large number of farmers need to be targeted. By targeting such farmers, extension agencies can facilitate and enhance the adoption of new technology/ICT among the farmers as such farmers are likely to affect the information decision process of more number of farmers from surrounding.

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