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Social network analysis approach to identify agricultural key communicators

T. Yamini[1], P. Venkatesan[2]*, V. Jyothi[1], M.R. Devy[1], V.S. Rao[3] and K. Suseela[4]

[1]*Department of Agricultural Extension Education, Agricultural College, Bapatla -522 101, India*
[2]*Extension Systems Management, ICAR-NAARM, Hyderabad -500 030, India*
[3]*Department of Statistics and Computer Applications, Agricultural College, Bapatla -522 101, India*
[4]*Department of Agricultural Economics, Agricultural College, Bapatla-522 101, India*

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***Corresponding Author Email :** venkatesan@naarm.org.in ***ORCiD:** https://orcid.org/0000-0002-8791-9858

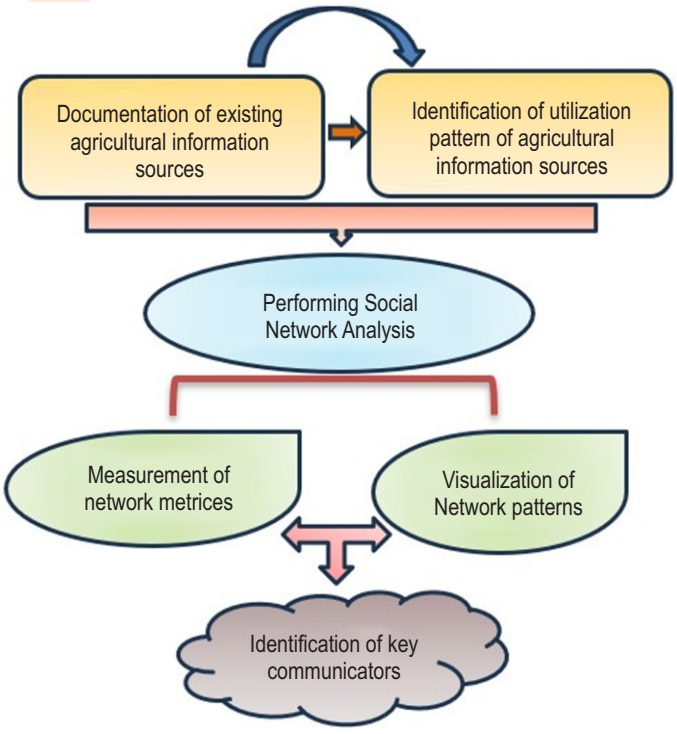
Abstract

Aim: This paper employed Social Network Analysis approach to visualize and calculate different social network metrics. It identifies key communicators who play pivotal roles in information flow.

Methodology: Research was conducted at Jammulapalem and Perali villages of Bapatla district, Andhra Pradesh, India, during 2022-23 using an exploratory research design. A total of 120 farmers Eigen vector were selected using simple random technique, and data was collected using a well-developed interview schedule. Network metrics such as Degree centrality, betweenness centrality, and eigen vector centrality were computed to evaluate the network structure using R software (version 4.3.1). R packages, namely igraph, statnet and network D3, were used for network creation, analysis and visualization to identify the influential nodes.

Results: The study revealed a complex web of relationships among various stakeholders within the agricultural network through a network graph, identifying key communicators with the highest Degree centrality.

Interpretation: The focal points identified through Social Network Analysis represent a specific demographic and socio-economic group, typically aged between 35 and 55, primarily medium-scale farmers,with landholdings spanning 10 to 25 acres and high annual income, with educational backgrounds ranging from high school to pre-university college, and wield significant influence within their local communities. They require sensitization, training, practical demonstrations, and personalized support to effectively disseminate agricultural information.



Key words: Agricultural Information System Network, Centrality measures, Information Sources, Key Communicators, Network visualization, Social Network Analysis,

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Introduction

In a dynamic landscape of agriculture, effective communication plays a pivotal role in disseminating information, fostering collaboration and driving innovation. As agriculture becomes increasingly complex and interconnected, the need to identify influential communicators, who act as central nodes in disseminating crucial information becomes paramount (Wang *et al.,* 2020). Understanding the structure of communication networks allows for more targeted and efficient dissemination of information enabling the development of strategies that harness the power of influential communicators. These key communicators are influential individuals within a community, possessing strong community ties and the ability to effectively share information and innovations. They bridge the gap between scientific innovations and local farmers by effectively disseminating new agricultural practices and technologies facilitating transfer of technologies. Thus, the identification of agricultural key communicators holds immense practical implications.

Social Network Analysis (SNA) is a methodology used to study social structures and relationships and it has a long history that spans several fields including sociology, anthropology, psychology and computer science. It is an innovative analytical tool which provides excellent scope to analyze complex networking system. SNA can be a valuable tool for agricultural extension agents to gain insights into the social dynamics of farming communities and design more effective and targeted interventions. Moreover, this SNA offers a comprehensive framework to study the patterns of interactions, information flow and influence within a network. Visualization and analysis of social network includes different metrics measures, i.e., Coefficient Clustering, Density, Closeness Centrality, Degree Centrality, Betweenness Centrality, etc. (Borgatti *et al*., 2006). These features are used to visualize the social networks. By applying SNA to the agricultural context, this research aimed to uncover the hidden structures and dynamics of communication networks

SNA can help to identify influential individuals or groups within a community who are respected and trusted by their peers. Agricultural extension agents can leverage these opinion leaders to disseminate information and promote adoption of new agricultural practices or technologies. Social ties are crucial for influencing the decision of farmers regarding the adoption of innovation (Singh *et al.,* 2017; Mishra *et al.,* 2019; Gupta *et al.,* 2020). It is imperative to identify the key factors in the farmers' information network to increase the spread of innovations as farmers share with each other the profitability and optimal use of agricultural innovations to cope up with the uncertainties associated with the new technologies. Hence, extension efforts should focus on farmers' social networks for promoting agricultural innovations (Khan *et al.,* 2017; Patel *et al.,* 2018; Yadav *et al.,* 2019; Sharma *et al.,* 2020). The knowledge on information networks may help extension functionaries to get sensitized to the critical roles played by central sources in the diffusion process. Besides, this will facilitate policy makers to deliver reliable information with the aid of these influential sources. In view of this, the study "Social Network Analysis Approach to Identify Agricultural Key Communicators" was taken up with the main objective to identify the key communicators using social network metrics.

Materials and Methods

The study was conducted during 2022-23 in Jammulapalem and Perali villages of Bapatla district of Andhra Pradesh state (Fig. 1) which were selected purposefully because of its practical aspects like accessibility, logistical viability and researchers' familiarity with the local language and place.The study area is located at an altitude of 7 m from the coast of Bay of Bengal. An exploratory research design was selected to perform the study. For the experiment, a total of 120 farmers were selected using simple random sampling technique. By consulting specialists and studying pertinent literature, a structured interview schedule was designed with consideration of the study's objectives and variables. Age, education, gender, land ownership, scientific orientation, economic drive, risk orientation, and innovativeness were the variables used for the study. The farmers were personally interviewed in an informal setting to obtain the primary data for the investigation by using the developed interview schedule. The farmers were asked to give their responses based on whom they would seek advice, information or suggestions regarding the aspects related to agriculture. The study was conducted in accordance with the ethical guidelines for human experiments as laid down in the Helsinki Declaration (World Medical Association, 2013; Malla and Bhat, 2016). The studies involving human participants were reviewed and approved by the competent authority of our institute. The participants provided their written informed consent to participate in this study.

The raw data was preprocessed including data cleaning to remove outliers and missing values before performing the analysis. An adjacency matrix was created from the data with nodes representing (individual respondent) and edges for (connections between the respondents). Numerous network metrics such as degree centrality, betweenness centrality and eigenvector centrality were computed in order to evaluate the network structure. These metrics were selected to identify the influential nodes within the network and to comprehend the information flow, similar procedure followed by (Pradhan *et al.* (2024). Statistical tools such as frequency, percentage, mean, standard deviation were used to interpret the findings and draw conclusions. Social network analysis was conducted using R software (version 4.3.1) using R packages, namely igraph, statnet and network D3 for network creation, analysis and visualization. The whole network properties were measured with the help of parameters like network size, total number of ties, average degree, network density and degree centrality.

Results and Discussion

The present study explored the personal, socio-economical and psychological characteristics of farmers using variables such as age, education, gender, land holding, scientific

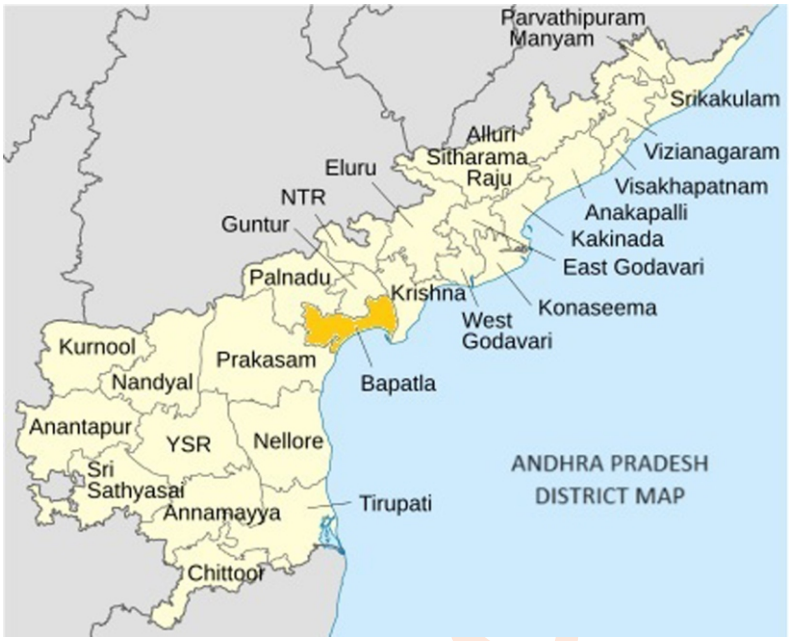

Fig. 1: Map depicting the locale of the study area.

orientation, economic motivation, risk orientation and innovation. The insights from the results (Table 1) indicated that nearly half (47.50%) of the respondents were old aged whereas 42.50% were middle aged and 10.00% young farmers. It was observed were indicated that majority (35.00%) of the farmers were illiterate whereas 20.00% of them were educated up to primary school level, followed by 18.34% of them with middle school level of education. Only 11.66% of the farmers had received education upto intermediate level, while 10.00% of them had studied upto high school level. A meager proportion of the respondents (5.00%) were graduates. The data highlighted a significant proportion of older farmers compared to younger ones with nearly half of the respondents being old-aged. This indicates a potential challenge concerning a need for policies and programs aimed at attracting and supporting younger individuals to enter and sustainably manage agricultural enterprises. The majority of farmers being illiterate or having only primary education underscores the educational disparities within the farming community. Limited education can hinder farmers' access to information, technology and market opportunities affecting their productivity and livelihoods. Addressing these educational gaps through adult literacy programs, vocational trainings and extension services can empower farmers with the knowledge and skills required to adopt modern farming practices and enhance their competitiveness (Bhosale and Kadam, 2021).

The results inferred that nearly half (46.67%) of the respondents were marginal farmers with land holdings up to 2.5 acres, followed by small farmers (37.50%) with landholdings ranging from 2.5 to 5 acres. While, 11.67 per cent of them had owned the land extending from 5 to 10 acres and were categorized as semi medium farmers, followed by 4.16 per cent of the farmers who were medium farmers with landholdings between 10 to 25 acres. This finding is in accordance with the study of Papnai *et al.* (2017), who reported that a majority of the respondents (53.33%) were marginal, followed by small (40.00%), medium (5.00%) and large (1.67%) category of land holding. The distribution of farmers according to landholding provided insights into the structure of landownership and farm sizes within the agricultural community. The observed distribution may be due to fragmentation of lands. Land is passed down through generations leading to subdivision and fragmentation over time. Social structures and power dynamics within rural communities might also influence access to land and opportunities for farm expansion.

The furnished data presented in Table 1 revealed that three fifth (60.00%) of the farmers had high economic motivation, while 31.67% and 8.33% of the farmers had medium and low level of economic motivation. It was also observed that majority (68.33%) of the farmers had medium level of innovativeness, while 21.67% and 10.00% of the farmers were categorized under high and low level of innovativeness, respectively. The results depicted that nearly half of the farmers (45.83%) belonged to the category of medium level of scientific orientation whereas 28.33% and 25.84% of the farmers had low and high level of scientific orientation. The results explained that about two-third of the farmers (63.34%) were tend to have medium orientation towards risk, while about 22.00% and 15.00% of the farmers had higher and low levels of orientation towards risk. Research findings have

Table 1: Socio-economic characteristics of the farmers

Category	Frequency	(n=120) %
Age		
Young age (18-35 yrs)	12	10.00
Middle age (35-50 yrs)	51	42.50
Old age (above 50 yrs)	57	47.50
Education level		
Illiterate (do not read and write)	42	35.00
Primary school (1st- 4th)	24	20.00
Middle school (5th- 7th)	22	18.34
High school (8th-10th)	12	10.00
PUC (11th- 12th)	14	11.66
Graduate	6	5.00
Landholding		
Marginal farmer (upto 2.50 acres)	56	46.67
Small farmer (2.51- 5.00 acres)	45	37.50
Semi medium farmer (5.01- 10.00 acres)	14	11.67
Medium farmer (10.01- 25.00 acres)	5	4.16
Economic motivation		
Low(<13.01)	10	8.33
Medium(13.01-17.39)	38	31.67
High(>17.39)	72	60.00
Innovativeness		
Low(<9.00)	12	10.00
Medium(9.00-14.10)	82	68.33
High(>14.10)	26	21.67
Scientific Orientation		
Low(<10.94)	34	28.33
Medium(10.94-16.71)	55	45.83
High(>16.71)	31	25.84
Risk Orientation		
Low(<7.70)	18	15.00
Medium(7.70-14.30)	76	63.34
High(>14.30)	26	21.66

identified farmers with medium levels of innovativeness and scientific orientation. The results are in line with the findings of Dixit *et al.* (2024), who reported that majority of the respondents had medium level of scientific orientation, economic motion and risk orientation. Targeted extension services and educational programs can improve technology uptake and knowledge dissemination within the farming community.

An exhaustive list of existing agricultural information sources in the locality was prepared based on farmers' responses and validation by experts. The AIS, namely, Village Agricultural Assistant (VAA)/ Village Horticultural Assistant (VHA), State Agricultural Extension Officials(AEO)/Agriculture Officers (AO)/ Horticulture Officers (HO), Acharya N. G. Ranga Agricultural University (ANGRAU) /District Agricultural Advisory and Transfer of Technology Centre (DAATTC) DAATTC/ Krishi Vigyan Kendra (KVK) Scientists, Bank officials, Agricultural Input Suppliers/ Dealers, Progressive farmers, fellow farmers / relatives, Market dealers acted as sources of informationof the whole network in the present study. The number of information sourcesfor analyzing the source use pattern was eight. The information source use pattern was examined to evaluate the source's effectiveness and competency with regard to information exchange (Table 2), including distribution of respondents' usage frequency as agricultural information sources for farming.

It was observed that VAA provided major information to the farmers in the AISN. Agricultural Input Suppliers/Dealers served as the second useful information source. The results showed that the third and fourth major sources of information were market dealers/ private agents and fellow farmers/ relatives/ neighbors, respectively. These sources are essential for practical insights and peer support. This is supported by Bahadur *et al.* (2021), who emphasized the role of social networks and market interactions in information dissemination. The Progressive farmers, Bank officials and AEO/AO/HO served as fifth, sixth and seventh useful source of information, respectively, underscoring their crucial role in disseminating agricultural knowledge and guidance. This finding aligns with the work of Joshi *et al.* (2018), who highlighted the importance of localized, accessible sources of information for effective agricultural practice. This suggests that while these sources are valuable, their impact may be limited compared to more direct and accessible information channels.

Table 2: Distribution of respondents' usage frequency of sources as agricultural information sources

Name of the sources	Frequency of Use						WMS	RANK
	Regular		Occasionally		Never			
	f	%	f	%	f	%		
VAA/VHA	114	95.00	6	5.00	0	0	2.950	I
State Agricultural Extension Officials (AEO/AO/HO)	16	13.33	47	39.16	57	47.50	1.658	VII
ANGRAU/DAATTC/ KVK Scientists	9	7.50	19	15.83	92	76.67	1.308	VIII
Bank officials	68	56.67	37	30.83	15	12.50	2.442	VI
Fellow farmers/ relatives/ neighbours	103	85.83	17	14.17	0	0	2.858	IV
Progressive farmers	87	72.50	24	20.00	9	7.50	2.650	V
Agricultural Input Suppliers/Dealers	112	93.33	8	6.67	0	0	2.933	II
Market dealers/ Private agents	96	80.00	23	19.17	16	13.33	2.917	III

f= frequency; % = percentage

Table 3: Whole network properties of Agricultural Information System Network at Perali village

Network property	Value
Network size	76
Total no. of. Ties	183
Average degree	3.25
Network density	0.86
Highest degree Centrality Score	13
Lowest degree centrality score	1
Highest closeness centrality score	0.0092
Lowest closeness centrality score	0.0035
Highest betweenness centrality score	115.40
Lowest betweenness centrality score	0.00

Likewise, ANGRAU/DAATTC/ KVK Scientists served as the least useful source of information possibly due to limited accessibility to farmers because of geographical distances, restricted outreach efforts, trust or familiarity issues, and communication gap (Fig. 2), as supported by Pradhan *et al.* (2024). This underscores the need for improved strategies to enhance the accessibility and trustworthiness of scientific advisory services to farmers.

VAA/ VHA and Agricultural Input Suppliers/Dealers act as central information source in the farming network. VAA/ VHA and Agricultural Input Suppliers/Dealers were identified as a key source of information, as farmers rely mostly on people who offer a one-stop-shop for a wide range of information related to farming, agricultural inputs including seeds, fertilizers, pesticides and machinery. Farmers have found it convenient to avail both their supplies and information at one place. The relationship that developed over time between farmers, VAA/ VHA and input dealers had made them the most trusted sources of information and advisors as they understand the local farming conditions and the specific needs of their customers. The results obtained from the SNA enabled the examination of types and patterns of relationship between sources where these sources visually represented in a network map as structural nodes connected with relationship (ties or links) between these nodes. The quantitative measures provided information regarding the functioning of the network as a whole. These measures depicted the nature of the entire network, its structure and degree of cohesion.Network centrality measures such as degree, closeness and betweenness centrality were assessed to identify the important nodes in farmers social networks and to highlight their significance and effectiveness. The studies of Choudhury *et al.* (2019) and Basera *et al.* (2021) support this finding. Choudhury *et al.* (2019) demonstrated that network centrality measures could effectively identify key sources within agricultural networks, emphasizing the importance of these sources in information dissemination and resource allocation. Their research showed that sources with high degree centrality were crucial for spreading innovations and best practices among farmers. Similarly, Basera *et al.* (2021) found that nodes with high closeness and betweenness centrality played pivotal roles in facilitating communication and collaboration within agricultural communities.

The representation of network size for this SNA (Fig. 3; Table 3) of Perali village, comprise 76 numbers inclusive of 60 farmer respondents and 8 agricultural information sources. The total numbers of ties or relation/ link was 183 which signifies the existing 183 connections between the nodes in the network. The average degree of the whole network was 3.25, which means the average of 3.25 connections were resent. The average degree was simply measured by calculating the average number of edges per node. The whole network density was 0.86 which implied that 86.00 per cent of direct relations existed among the

Table 4: Identified key communicators of Perali village and their characteristics

Network property	Key nodes	Role	Characteristics
Degree Centrality	p7, p8, p37, p66	Influential leaders	▪ Old age (45 to 70 years) ▪ Had medium to high school level of education ▪ Land holdings ranging from 7 to 10 acres, high annual income ▪ High social participation and medium level of psychological attributes.
Closeness centrality	p46, p8, p39, p48, p18	Central nodes	▪ Old age (50 to 60 years) ▪ Had primary to high school level of education ▪ Average land holdings of 10 to 12 acres, high annual income ▪ High social participation and medium level of psychological attributes.
Betweenness centrality	p8, p18, p66, p46, p48	Bridges or Gate keepers	▪ Middle age (30 to 58 years) ▪ Had high to intermediate level of education ▪ Land holdings ranging from 8 to 10 acres, high annual income ▪ High social participation, extension contact and medium to high level of psychological attributes.
Highest Centrality (degree, closeness, betweenness or combination of two)	p8, p18, p46, p48	Prestigious, most influential and key informants	▪ Middle age category (30 to 58 years) ▪ Had high to intermediate level of education ▪ Average land holdings ranging of 10 acres, high annual income ▪ High social participation and extension contact and medium level of psychological attributes.

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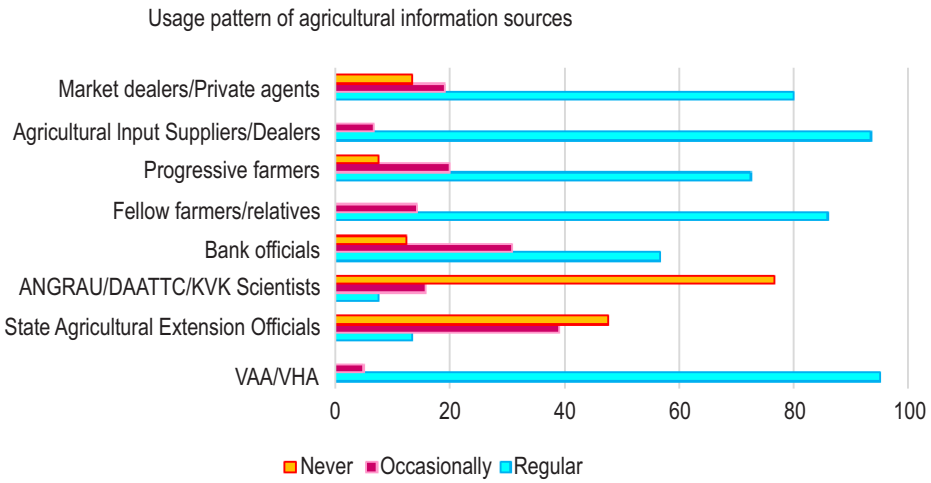

Fig. 2: Usage pattern of Agricultural Information Sources.

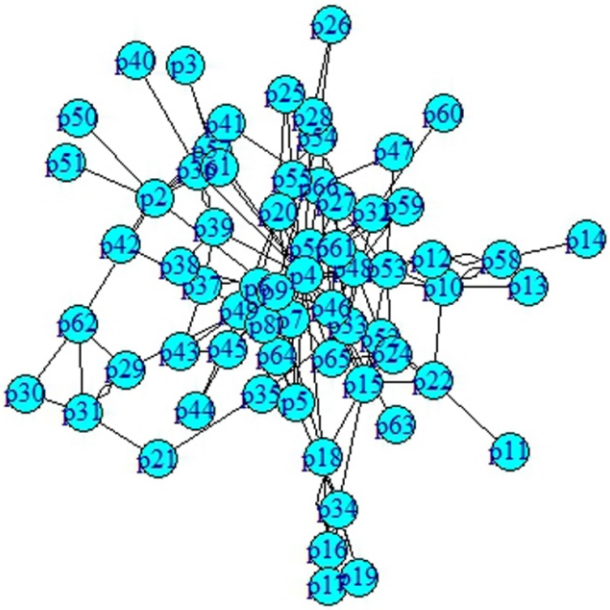

Fig. 3: Existing AISN at Perali village.

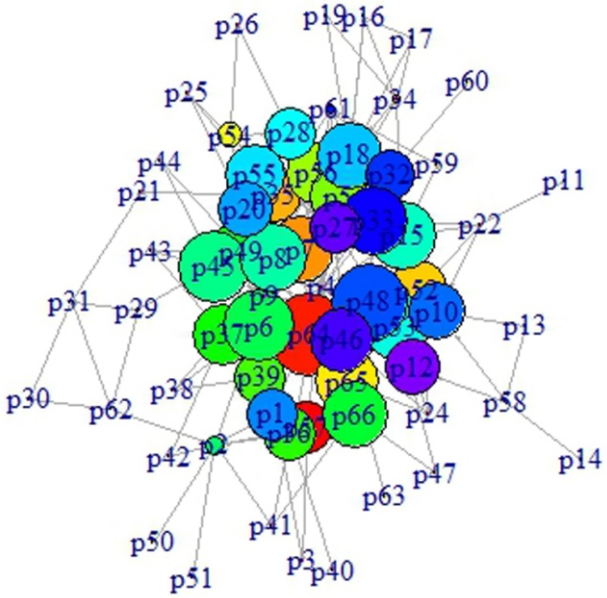

Fig. 4: Graph representing the key nodes of Perali village based on Centrality measures.

sources. Degree centrality represents the number of connections (edges) for a node. The more edges within the graph, the more important the node. The highest degree score of 13 indicated that the maximum number of connections that a node had in the whole network was 13, while the lowest degree score of 1 indicated that the minimum number of connections that a node had in the whole network was 1. Closeness centrality provide insights into the relative importance or accessibility of individuals within a network.High closeness centrality indicates the nodes that act as central points of information exchange or influence. In contrast, low closeness centrality may suggest nodes that are less influential or peripheral within the network.

The highest closeness centrality score of the network was 0.0092. As mentioned (Table 3), the network had the lowest closeness centrality value of 0.0035. Betweenness centrality values highlight the nodes that serve as important connectors between different parts of the network. Vertices with high

Table 5: Whole Network properties of AISN at Jammulapalem village

Network property	Value
Network size	72
Total no. of. ties	173
Average degree	4.41
Network density	0.67
Highest degree Centrality Score	10
Lowest degree centrality score	1
Highest closeness centrality score	0.0081
Lowest closeness centrality score	0.0033
Highest betweenness centrality score	102.41
Lowest betweenness centrality score	0.00

betweenness centrality values (115.40) act as bridges or bottlenecks in the network. They are crucial for maintaining connectivity between different parts of the network. Based on the inference drawn from Table 4, the identified influential leaders with highest in-degree centrality in the network were node p7, p8, p37 and p66 and were referred as "influential nodes"who have the most direct connections with others in the network, making them crucial for disseminating information and innovations effectively. Nodes p46, p8, p39, p48 and p18, with the highest closeness centrality were often referred to as "central nodes" reflecting their significance in the network due to their ability to reach other nodes efficiently and quickly. They serve as pivotal points for information flow and influence within the network. The nodes with higher betweenness centrality values, such as node p8, p18, p66, p46 and p48, appeared on many shortest paths between other nodes. Hence, they were considered as bridges or bottlenecks in the network. It was observed that nodes p8, p18, p46 and p48, belonged to all three categories of high centrality metrics or at least a combination of two- degree, betweenness and closeness, indicated that these individuals occupy a particularly influential and central position within the agricultural social network.

Based on the interpretation of a SNA graph (Fig. 4) with key nodes represented as large size nodes and different colors depicted the significance and relationships of the nodes.Larger nodes typically indicated higher centrality or importance within the network. Centrality metrics such as degree centrality (number of connections), betweenness centrality (importance as a bridge between other nodes) and closeness centrality (importance of connections to other important nodes) were used to determine the node size. So, larger nodes were the most influential or central individuals/entities within the network. Different colors of the nodes represented different attributes or characteristics of the nodes. Nodes of the same color belonged to same community or possessed similar attributes within the network.

The SNA of AISN (Fig. 5; Table 5) represented in Jammulapalem village, showed network size of 72, consisting 60 farmer respondents and 8 agricultural information sources. The total number of ties or relation/ link was 173, which signifies the existing 173 connections between the nodes in the network. The average degree of the whole network was 4.41, which means that the average of about 4 connections were present. The average degree was simply measured by calculating the average number of edges per node. The whole network density was 0.67, which implies that 67.00 per cent of direct relations existed among the sources. Degree centrality represents the number of connections (edges) for a node. The more edges within the graph, the more important the node. The highest degree score of 10 indicated that the maximum number of connections that a node had in the whole network was 10, while the lowest degree score of 1 indicated that the minimum number of connections that a node had in the whole network was 1. Closeness centrality provides insights into the

Table 6: Identified key communicators of Jammulapalem village and their characteristics

Network property	Key nodes	Role	Characteristics
Degree Centrality	j6, j32, j22, j40	Influential leaders	▪ Old age (50 to 75 years) ▪ Had primary to high school level of education ▪ Land holdings ranging from 5 to 10 acres, high annual income ▪ High social participation and medium level of psychological attributes.
Closeness centrality	j21, j28, j32, j40, j49	Central nodes	▪ Old age (40 to 60 years) ▪ Had medium to high school level of education ▪ Average land holdings of 7acres, medium annual income ▪ High social participation and medium level of psychological attributes.
Betweenness centrality	j8, j32, j28, j49, j21	Bridges or Gate keepers	▪ Middle age (35 to 55 years) ▪ Had high to intermediate level of education ▪ Land holdings ranging from 8 to 12 acres, high annual income ▪ High extension contact and medium to high level of psychological attributes.
Highest Centrality (degree, closeness, betweenness or combination of two)	j32, j28, j49, j21	Prestigious, most influential and key informants	▪ Middle age category (35 to 55 years) ▪ Had high to intermediate level of education ▪ Average land holdings ranging of 10 acres, high annual income ▪ High extension contact and medium level of psychological attributes.

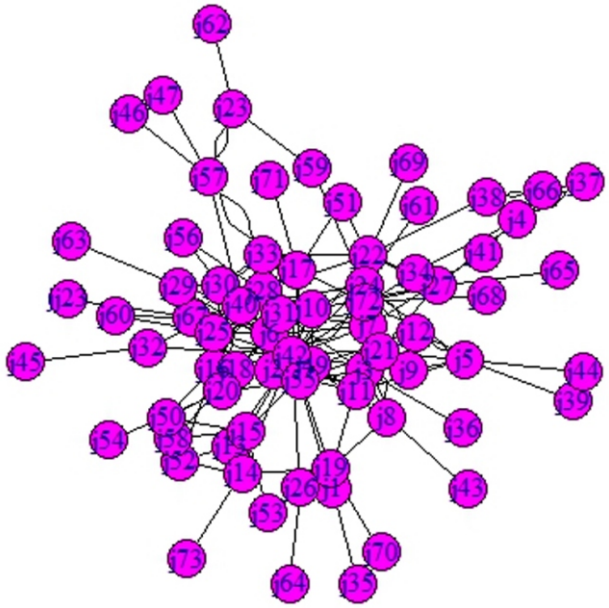

Fig. 5: Existing AISN at Jammulapalem village.

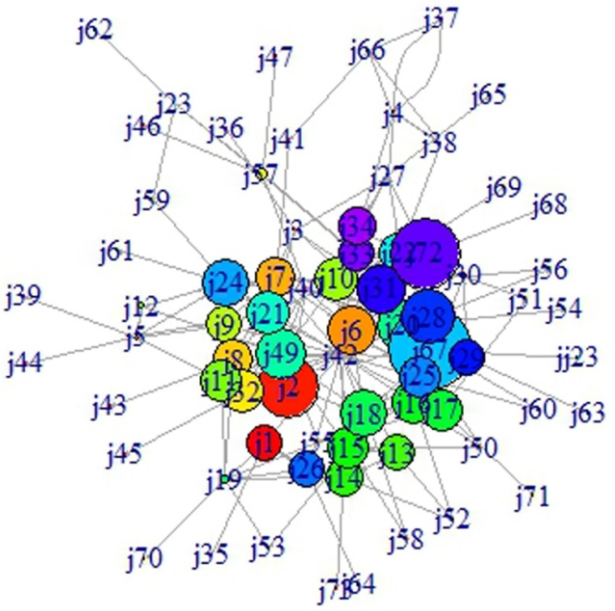

Fig. 6: Graph representing the key nodes of Jammulapalem village based on Centrality measures.

relative importance or accessibility of individuals within a network. High closeness centrality indicates the nodes that act as central points of information exchange or influence. In contrast, low closeness centrality may suggest nodes that are less influential or peripheral within the network. The highest closeness centrality score of the network was 0.0081. As mentioned in Table 5, the network had the lowest closeness centrality value of 0.0033. Betweenness centrality values can provide insights into the overall structure of the network, highlighting nodes that serve as important connectors between different parts of the network. Vertices with high betweenness centrality (102.41) values act as bridges or bottlenecks in the network. They are crucial for maintaining the connectivity between different parts of the network.

Based on the inference drawn from Table 6, the identified influential leaders with highest in- degree centrality in the network were nodes, j6, j32, j22 and j40 and were referred as “influential nodes”who had direct connections with others in the network, making them crucial for disseminating information and innovations effectively. Nodes j21, j28, j32, j40 and j49, with the highest closeness centrality are often referred to as "central nodes" reflecting their significance in the network due to their ability to reach other nodes efficiently and quickly. They serve as pivotal points for information flow and influence within the network. The nodes with higher betweenness centrality values such as node j8, j32, j28, j49 and j21, appeared on many shortest paths between other nodes. Hence, they were considered as bridges or bottlenecks in the network. It was observed that nodes j32, j28, j49 and j21, belonged to all three categories of high centrality metrics or at least a combination of two-degree, betweenness and closeness, indicated that these individuals occupy a particularly influential and central position within the agricultural social network.

Based on the interpretation of SNA graph (Fig. 6) with key nodes represented as large size nodes and different colors depicted the significance and relationships of the nodes. Larger nodes typically indicated higher centrality or importance within the network. Centrality metrics such as degree centrality (number of connections), betweenness centrality (importance as a bridge between other nodes) and closeness centrality (importance of connections to other important nodes) were used to determine node size. So, larger nodes were the most influential or central individuals/entities within the network. Different colors of the nodes represented different attributes or characteristics of the nodes. Nodes with similar color belonged to same community or possessed similar attributes within the network. Nodes were colored based on attributes such as gender, profession, age group, annual income or any other relevant categorization. The studies of Pradhan *et al.* (2024) and Basera *et al.* (2021) support the above findings. The network roles played by these key nodes were identified as influencers, key communicators, central nodes, opinion leaders, bridges or gate keepers based on their centrality scores indicating their extent to dominate the network by influencing and communicating agricultural information in the network (Basera *et al.,* 2021). Farmers with highest degree centrality are those who are most connected to other farmers and considered influential, respected and trusted by their peers within their community. Their opinions, actions and recommendations were often highly regarded by other farmers, as they can have a significant impact on adopting of new practices, technologies or policies within the community. These nodes can be utilized at

various stages of agricultural development and management. These farmers can be engaged during pre-season planning for sharing information on crop selection, planting techniques and input procurement, and can be utilized throughout the growing season for disseminating pest management strategies, weather updates and agronomic advice. Consulting them during policy formulation and implementation stages to ensure the inclusion of grassroots perspectives and effective dissemination of policy-related information.

Individuals with highest betweenness centrality serve as crucial connectors between different parts of a network and aid in transferring knowledge and disseminating innovations to farmers and agricultural practitioners. They can bridge the gap between researchers, extension services and farmers and have the potential to influence the spread of innovations and ideas throughout the entire agricultural network. These farmers can be engaged as key messengers for disseminating information about new technologies, best practices, market opportunities and government programs to the wider agricultural community. They can be best utilized at awareness stage of adoption and to facilitate market access for farmers by connecting them with buyers, distributors and agribusinesses and to promote supply chain integration by disseminating information about efficient logistics, storage and transportation practices as well as opportunities for value addition and product diversification (Estrada and Bodin, 2008). Farmers with highest closeness centrality are closest and easily accessible to a large number of farmers in the network. Others farmers can be suggested to visit these farmers to learn about new farming techniques, pest management strategies or climate-smart practices. They can be targeted for rapid dissemination of urgent information such as disease outbreaks, weather alerts, market fluctuations or government regulations by leveraging their close connections to reach a wider range of farmers in need.

Based on the interpretation of centrality scores it was observed that a considerable proportion of farmers belonged to all three categories of high centrality metrics-degree, betweenness and closeness indicated that these individuals occupied a particularly influential and central position within the agricultural social network. When a farmer score high in all three categories, it means they not only have a large number of direct connections (high degree centrality), but they also act as important intermediaries between different groups (high betweenness centrality) and are closely connected to the rest of the farmers (high closeness centrality). These are the farmers who are quick to adopt new technologies, practices or innovations and are often sought out by others for advice and guidance. These individuals can be utilized as catalysts for positive change. Their unique position can be practically utilized in agriculture for disseminating production practices such as crop rotation, soil conservation techniques, water management strategies, Integrated Pest Management (IPM) practices, etc. Moreover, these farmers can be recommended as farmer friends or contact farmers in ATMA program.These farmers have the ability to actively engage in sharing information and experiences, can easily collaborate with others and has access to up-to-date information from agricultural experts can be made to adopt agricultural technologies such as drip irrigation systems, precision farming equipment and biotechnology-enhanced crop varieties (Kumar and Sinha, 2021). Upon their adoption, these farmers can be technically trained to organize field demonstrations, technology showcases workshops, facilitate technology demonstrations, provide hands-on training to fellow farmers and knowledge-sharing sessions where farmers can learn from their experiences and expertise and thus, aid in the promotion and adoption of agricultural technologies.

The key nodes identified through Social Network Analysis (SNA) represented individuals within a specific demographic and socio-economic profile. These individuals typically fall within the age group of 35 to 55, possessed educational qualifications ranging from high school to pre-university college (PUC) level, and were characterized as medium-scale farmers with an average land holdings of 10 acres. Additionally, they exhibited high annual income. The results corroborate the findings of Basera *et al.* (2019), who reported that majority of the opinion leaders belonged to middle age category, educated upto primary school and had medium socio-economic status. This demographic range of age between 35 to 55 suggested that the individuals identified as key nodes are likely to be in the prime of their professional and personal lives. They might have accumulated a significant amount of experience and expertise in their respective fields making them influential within their networks. The educational qualifications ranging from high school to PUC level indicate that these individuals had acquired a foundational level of education.

The educational background indicated that these individuals might have practical knowledge and skills relevant to their occupations, but they may not have pursued higher education. Hence, these farmers can be empowered by organizing training programs and educational materials that are tailored to the educational background and learning preferences of farmers with medium education levels and by using simple language, visuals and practical demonstrations to explain complex technologies in a way that is easy to understand and implement, provide personalized support services to help farmers overcome specific barriers to technology adoption, etc. The characterization of key nodes as medium-scale farmers with an average landholding of 10 acres signify their pivotal role in the agricultural landscape. Their relatively larger land holdings imply a certain level of resource access, economic stability, agricultural productivity and influence within the agricultural community, potentially making them important sources in local agricultural networks. High annual income among key nodes highlights their economic significance, indicating their capability to invest in agricultural inputs, adopt innovations, and contribute to community growth. Interpreting these characteristics collectively, these nodes represent mature, experienced individuals with significant economic influence, playing crucial roles in shaping information,

resources, and decisions within their agricultural networks.

Thus, it can be concluded that identified key communicators, with highest centrality scores across all metrics (degree, betweenness and closeness), underscore the need to enhance the existing network for improved information, resource, and expertise exchange to benefit village development. Sensitizing and training key informants within existing groups can optimize their role in disseminating agricultural information, facilitating more effective introduction of innovations and technologies. Leveraging their influence, connectivity and accessibility, these individuals can serve as early adopters, influencing wider adoption within the agricultural community.

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References

Bahadur, R., N. Bhardwaj and S. Kashyap: Understanding the role of social networks in the adoption of sustainable agricultural practices: A case study in rural Uttar Pradesh. *J. Sustain. Agricul.,* **45**, 321-335 (2021).

Basera, N., N. Bhardwaj and A. Huria: Information seeking behaviour of opinion leaders in hill region of Uttarakhand. *J. Krishi Vigyan,* **8**, 154-161(2019).

Basera, N., A. Huria and N. Bhardwaj: Applying centrality measures to identify network roles of farm women in hill region of Uttarakhand, India. *Indian J. Ext. Edu.,* **57**, 140-144 (2021).

Bhosale, G. B. and Kadam R. P.: Characteristics of farmers using the information and communication technology for seeking agricultural information. *Ind. J. Pure App. Biosci.*, **9**, 158-162 (2021).

Borgatti S.P., M.C. Kathleen and K. David: On the robustness of centrality measures under conditions of imperfect data. *Social Networks*, **28**, 124-136 (2006).

Choudhury, A. and A. Rai: Exploring social network structures among smallholder farmers for enhancing agricultural extension services in Assam, India. *J. Agric. Educ. Ext.,* **25**, 411-425 (2019).

Dixit, A., N. R. Meena, R. K. Doharey, A. Verma, Y. Pateriya and A. Kumar: A study on socio-economic profile of paddy growers in Milkipur Block of Ayodhya District of Uttar Pradesh, India. *Asian J. Agricul. Exten. Econo. Sociol.,* **42**, 137-148 (2024).

Estrada, E. and O. Bodin: Using network centrality measures to manage landscape connectivity. *Ecol. Applica.,* **18**, 1810-1825 (2008).

Gupta, S., R. Singh and P. Mishra: Leveraging social networks for technology adoption among farmers: Evidence from Uttar Pradesh, India. *Agric. Syst.,* **183**, 102870 (2020).

Joshi, A., R. Sharma and S. Patel: Analyzing social network patterns for knowledge sharing among dairy farmers in Gujarat, India. *Int. J. Dairy Technol.,* **71**, 1033-1043 (2018).

Khan, A., A.Kumar and P. Singh: Role of social networks in information dissemination among vegetable growers: A case study in Haryana, India. *Indian J. Agric. Sci.,* **87**, 362-367 (2017).

Kumar, P. and A. Sinha: Information diffusion modeling and analysis for socially interacting networks. *Soc. Netw. Anal. Min.,* **11**, 11 (2021).

Malla, A.A. and N.M. Bhat: Ethics in psychiatric research: Issues and recommendations. *Int. J. Indian Psychol.,* **3,** 243-257 (2016).

Mishra, S., A. Sahu and S. Patra: Impact of social networks on adoption of improved agricultural practices: A study among rice farmers in Odisha, India. *Int. J. Agric. Manag. Dev.,* **9**, 235-243 (2019).

Papnai, G., N.Bhardwaj, S.K. Kashyap and S. Sunetha: Socio-personal, communication characteristics and information needs of vegetable growers of hill region of Uttarakhand. *J. Krishi Vigyan,* **6**, 191-196 (2017).

Patel, R. and V. Singh: Examining the influence of social networks on crop choice decisions among farmers in Madhya Pradesh, India. *J. Crop Improv.,* **32**, 645-658 (2018).

Pradhan, K., J.K. Chauhan and B. Ganguly: Heeding the euphony of Agricultural Information System Network (AISN) in the Eastern Region of India: A Social Network Analysis (SNA) study. *Indian Res. J. Ext. Edu.,* **24**, 1- 11 (2024).

Sharma, N and D. Mishra: Social network analysis of information sharing among dairy farmers in Rajasthan, India. *Indian J. Dairy Sci.,* **73**, 82-87 (2020).

Singh, A., R. Yadav and A. Srivastava: Role of social networks in technology adoption: A case study of wheat farmers in Punjab, India. *Indian J. Agric. Econ.,* **72**, 360-371(2017).

Wang, W., J. Wang, K. Liu and Y.J. Wu: Overcoming barriers to agriculture green technology diffusion through stakeholders in China: A social network analysis. *Int. J. Environ. Res. Public Hlth.,* **17**, 6976 (2020).

World Medical Association Declaration of Helsinki: Ethical Principles for Medical Research Involving Human Subjects. *J. American Med. Assoc.,* **10**, 2191–2194 (2013).

Yadav, S., V. Chauhan and R. Sharma: Exploring the impact of social networks on agricultural innovations adoption: A study among maize farmers in Bihar, India. *Agric. Econ. Res. Rev.,* **32**, 307-317 (2019).

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