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Mapping information flows: A social network analysis of Kudumbashree JLG women farmers

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Abstract

The dissemination of agricultural knowledge in India is constrained by the limited outreach of public extension systems, compelling farmers to rely on both institutional and informal contacts. This study employs Social Network Analysis (SNA) to map and compare the information flow structures among Kudumbashree Joint Liability Group (JLG) women farmers in the districts of Thiruvananthapuram and Kollam, Kerala. Primary data from 50 respondents were analysed using Gephi (v0.10.1) to assess network-level properties (density, size, ties, isolates) and node-level centrality measures (degree, closeness, betweenness). The analysis revealed distinct network architectures: the Thiruvananthapuram network was JLG-centric but reliant on a single informal broker, making it larger yet fragile. In contrast, the Kollam network was denser, more integrated, and featured multiple brokers from both institutional and informal sources. The findings indicate that while neighbours and local farmers are the most accessible information sources, institutional actors like Agricultural Officers and cooperatives provide critical structural stability and credibility. The study concludes that strengthening synergistic linkages between formal and informal actors is essential for creating more resilient, inclusive, and effective agricultural knowledge systems, and recommends targeted extension strategies to integrate peripheral actors.

Keywords: Social network analysis, Kudumbashree, joint liability groups, women farmers, information networks, Kerala

Introduction

Agricultural knowledge delivery in India faces persistent challenges due to limited extension outreach. With one extension worker often responsible for supporting over a thousand farm households, farmers rarely receive timely, location-specific advice (Singh, 2019; Riaz *et al*., 2022) [25, 22]. Adoption of agricultural innovations depends not only on technology but also on the accessibility and credibility of information sources (Kumar *et al*., 2022) [16].

Farmers usually depend on a blend of formal institutions such as cooperatives, input dealers, banks, and agricultural officers, alongside informal sources like neighbours, friends and relatives. Prior research indicates that input dealers frequently emerge as dominant advisors in production and marketing (Negi *et al*., 2018) [19], while cooperatives and producer organizations provide access to credit and organizational strength (Joseph *et al*., 2016) [15]. Extension service providers as Gram Sevaks and KVK scientists are important but their reach remains limited due to limited staff strength (Meena *et al*., 2012) [17].

Most research studies on information-seeking behaviour assess frequency of use or classify farmers as low, medium, or high users (Riaz *et al*., 2022; Vishnu *et al*., 2019) [22, 32]. While these approaches offer valuable insights into individual preferences, they possess a significant limitation: they fail to capture the relational architecture and structural dynamics of the information systems themselves. A more nuanced understanding of knowledge diffusion requires analysing how these actors are interconnected, moving beyond individual usage to map the network's topology. Identifying central figures (hubs), brokers (who bridge structural holes), and peripheral actors is therefore essential for diagnosing knowledge flows and potential bottlenecks (Jagriti *et al*., 2021) [14]. It is this critical gap in the literature that the present study addresses and applied Social Network Analysis (SNA) to map institutional and informal linkages of Kudumbashree JLG (Joint Liability Group) women farmers. SNA provides actor-level and network-level measures including degree, betweenness, and cohesion, enabling identification of opinion leaders and bridging actors (Singh *et al*., 2019) [26]. By employing this approach, the study contributes insights into the structure of JLG women farmer networks in Kerala.

Theoretical background of social network analysis (SNA)

Social Network Analysis (SNA) is a methodological framework that examines the structure of relationships among actors and how these structures influence information exchange, decision-making, and innovation diffusion. It is based on the principle that farmers' access to agricultural knowledge and services is not determined by individual characteristics alone, but by their position within the wider social and institutional network (Jagriti *et al*., 2021) [14].

SNA provides tools to assess both actor-level properties and whole-network properties. Among actor-level measures, degree centrality indicates the number of direct ties and reflects the popularity or activity of an actor, betweenness centrality captures brokerage roles by identifying actors who bridge disconnected subgroups, and eigenvector centrality highlights influence through association with other central actors. At the network level, properties such as density, cohesion, and core-periphery structure describe how well the system is integrated and how efficiently information flows.

In the agricultural extension context, SNA has been increasingly applied to identify opinion leaders, brokers, and peripheral actors in farmer communities. For example, Jagriti *et al*. (2021) [14] mapped farmer networks in rainfed areas and found that informal actors played a crucial role in information acquisition. Similarly, Vishnu *et al*. (2019) [32] highlighted the role of network structures among livestock farmers in shaping knowledge diffusion. In Kerala, studies have also shown how institutional and informal contacts interact in the spread of agricultural knowledge, with cooperatives, input dealers, and peer farmers functioning as important information nodes (Sebastian & Jeyalakshmi, 2019) [24].

These applications demonstrate that SNA is not only a theoretical framework but also a practical tool for strengthening extension systems. By identifying central hubs, bridging actors, and isolates, SNA helps design targeted interventions that make information dissemination more inclusive, efficient, and responsive to farmers' needs.

Methodology

Study area

The study was carried out during 2024-25 in the districts of Thiruvananthapuram and Kollam in Southern Kerala. These districts were purposively selected owing to the high concentration of active agricultural joint liability groups (JLGs) operating under the Kudumbashree mission. The JLG model, introduced by NABARD, refers to a collective of 4-10 individuals from similar socio-economic backgrounds who come together to access institutional credit under a shared liability framework. This "joint liability" mechanism enables members without individual collateral to avail credit by mutually guaranteeing loan repayment, thereby minimizing lender risk (Reserve Bank of India, 2015) [21].

Women-based JLGs in these districts are highly engaged in crop cultivation, livestock rearing, and allied agricultural enterprises. Their collective functioning relies on mutual support, frequent communication, and coordinated decision-making, making them suitable for examining information flows and network structures. Studying women farmers within these institutional groups addresses a critical gap, as they play a central role in everyday agricultural operations yet remain underrepresented in empirical research on information exchange and digital engagement (Singh *et al*., 2020) [27].

Sampling procedure

A purposive sampling strategy was adopted for selecting respondents from active agricultural JLGs. Social network analysis (SNA) emphasizes capturing the completeness and accuracy of a bounded network rather than relying on random or statistically representative sampling (Borgatti *et al*., 2018) [7]. Therefore, respondents were purposively selected based on their active involvement in farming and frequent interactions with diverse agricultural information sources.

A total of 40 women farmers were selected for the study, comprising 20 respondents each from Thiruvananthapuram and Kollam. Respondents were drawn from JLGs that were operational, meeting regularly, and directly engaged in agricultural activities. This ensured that the identified actors were part of meaningful communication networks relevant to digital and agricultural information exchange.

Instrument and data collection

Primary data were collected using a structured and pre-tested interview schedule developed based on a review of literature, expert consultation, and field validation in the study area. The instrument included sections on socio-personal characteristics, group participation, access to agricultural information, digital literacy indicators, and network interactions. Both closed and open-ended questions were used to capture the nature, strength, and frequency of information exchange between JLG members and external actors.

Network data were collected by asking respondents to identify their key sources of agricultural information individuals, institutions, and digital platforms and to rate the frequency and effectiveness of these contacts. This enabled the construction of adjacency matrices and directional ties required for network mapping and analysis.

Statistical analysis

Social network analysis (SNA) was carried out to understand the structure, strength, and dynamics of information exchange among the respondents and key agricultural actors. The data obtained through the interview schedule were converted into adjacency matrices representing the direction and intensity of communication ties. These matrices were imported into Gephi (version 0.10), an open-source network analysis and visualization software, for further analysis.

Gephi was used to compute major network parameters, including:

- Degree centrality (in-degree and out-degree) to identify highly connected information actors.
- Betweenness centrality to understand bridging roles and information brokers in the network.
- Closeness centrality to assess the relative accessibility of actors within the network.
- Network density to determine the overall connectedness of the JLG information system.
- Modularity and community detection to identify clusters or sub-groups within the JLG networks.

Visual network maps were generated using the forceatlas2 layout algorithm in Gephi to depict communication pathways, central actors, and structural patterns within the information networks. Visualizations were refined through adjustments to node size, edge weight, and colour coding to represent actor centrality and tie strength.

The use of Gephi enabled a comprehensive understanding of how information flows within and across JLG groups, the influence of central actors, and the level of cohesion and fragmentation in the agricultural communication network.

Results and Discussion

Social Network Analysis (SNA)

The application of SNA is particularly suited to this research as it moves beyond simply counting information sources to instead map the intricate structure of relationships through which knowledge flows. This allows for the identification of which actors hold influential positions, control information, or bridge disconnected parts of the network—insights that traditional frequency-based analyses cannot provide (Wasserman & Faust, 1994) [33].

The elicited information on farmer-institution linkages was organized into a two-mode (affiliation) adjacency matrix, where rows represented farmers and columns represented information sources. This matrix was then converted into a one-mode matrix to analyse the inter-relationships among the institutions themselves based on shared referrals from farmers.

Key network parameters were computed at both the network and node (actor) level to address the study's objectives and characterize the system's structure:

Network-Level Measures

- Density: Calculated as the proportion of actual ties to all possible ties, providing a measure of the overall interconnectedness and cohesion within the network.
- Network Size: Defined as the total number of nodes (individuals and institutions) identified in the network.
- Number of Ties: The total count of connections between nodes, reflecting the volume of potential information and resource flow.
- Number of Isolates: The count of nodes with no connections, which is critical for identifying farmers or institutions completely disconnected from the information network.
- Average Degree: The mean number of connections per node, representing the overall level of connectivity and participation.

Node-Level Measures (Centrality Metrics)

- **Degree Centrality:** Measured the number of direct connections a node has.
- **Closeness Centrality:** Measured the average shortest path from a node to all other reachable nodes. Nodes with high closeness can access or disseminate information quickly through the network, indicating independence from brokers. The maximum and minimum values were computed to identify the most and least central nodes in this regard.
- **Betweenness Centrality:** Quantified the number of times a node acts as the shortest bridge between two other nodes. This metric is crucial for identifying brokers or gatekeepers who control information flow and connect otherwise disparate parts of the network. The maximum and minimum values were calculated to pinpoint the key intermediaries and the most peripheral actors.

Data processing, matrix analysis, and network visualization were performed using Gephi software (v0.10.1), a robust tool validated for similar agricultural SNA studies (Jagriti *et al*., 2021; Yamini *et al*., 2024) [14, 36].

The Social Network Analysis of Kudumbashree JLG women farmers in Thiruvananthapuram and Kollam districts revealed contrasting structures of information exchange (Fig. 1 & Fig. 2).

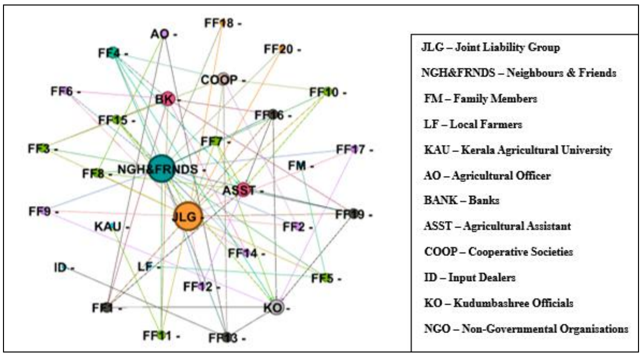

Fig 1: Social network of Kudumbashree JLG women farmers in Thiruvananthapuram

In Thiruvananthapuram, JLGs emerged as the most central actors, acting as the key hub of information flow within the network. Neighbours and friends played important brokerage roles by linking otherwise unconnected members, thereby supporting peer-to-peer knowledge transfer. Such brokerage positions are critical for innovation diffusion, as highlighted by Bandiera and Rasul (2006) [4] and Gladwin *et al*. (2001) [11]. Despite this, a few farmers were positioned at the margins, suggesting limited participation and possible risks of exclusion from digital knowledge sharing, consistent with Doss (2018) [8] who noted that marginal actors often face information constraints.

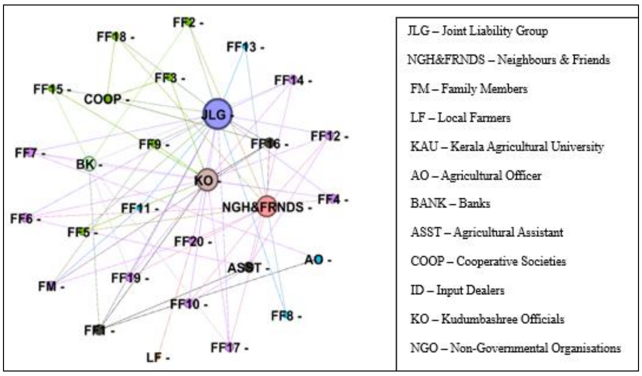

Fig 2. Social network of Kudumbashree JLG women farmers in Kollam

In Kollam, the network appeared relatively denser and more institutionally integrated. JLGs not only occupied the most central positions but also acted as brokers, reinforcing their dual role as both leaders and connectors. This duality has been observed in other collective networks where institutions act as both sources and mediators of information (Spielman *et al*., 2011; Pingali, 2012) [29, 20]. Alongside JLGs, institutional actors such as cooperatives, banks, and agricultural assistants emerged as secondary hubs of interaction, confirming the role of formal organizations in enhancing farmer connectivity (Aker, 2011) [2]. In addition, a few farmers acted as bridging nodes, connecting subgroups and enhancing the cohesion of the overall network, a pattern consistent with the "strength of weak ties" theory (Granovetter, 1973; Rogers, 2003) [13, 23].

The comparison indicates that while Thiruvananthapuram networks were JLG-centric but supported by informal brokers, Kollam's network was more diversified and institutionally driven. In both cases, the presence of peripheral actors highlights the need for targeted extension efforts to ensure equitable diffusion of digital literacy across all members (Munshi, 2004; World Bank, 2021) [18, 35].

Table 1: Comparative overview of various ego network measures of JLG women farmers in two districts.

Properties		Thiruvananthapuram	Kollam
Density		0.163	0.172
Network size/No.of nodes		31	29
No.of ties		76	70
Isolates		0	0
Avg.Degree		4.90	4.83
Degree centrality	Maximum Value	19	20
	Minimum Value	1	1
Closeness centrality	Maximum Value	0.682	0.778
	Maximum Value	0.326	0.333
Betweeness centrality	Maximum Value	143.48	174.25
	Minimum Value	0.00	0.00

Network Properties

- Density measures the proportion of actual connections in the network relative to all possible connections. Both Thiruvananthapuram (0.163) and Kollam (0.172) networks displayed low density values, suggesting that although information sharing is present, the networks remain relatively sparse. Similar low-density structures in farmer networks have been associated with slower diffusion of innovations (Freeman, 1979; Wood *et al*., 2014) [10, 34]. The slightly higher density in Kollam indicates a marginally stronger level of connectivity and more frequent exchanges, which align with findings from FAO (2017) [9] on the role of stronger ties in knowledge diffusion.
- Network size refers to the number of actors (nodes) included in each network. Thiruvananthapuram had 31 actors, while Kollam had a slightly smaller network of 29 actors. While larger networks generally provide more opportunities for information flow, the effectiveness of information dissemination depends more on structural connectivity than size alone (Valente, 2010) [31].
- Number of ties represents the total number of connections or relationships among actors. Thiruvananthapuram reported 70 ties and Kollam also had 70 ties, showing that farmers in both districts maintained active linkages despite slight differences in network size. Active ties are critical for knowledge sharing, echoing Spielman *et al*. (2011) [29] who emphasized that dense interaction strengthens collective action.
- Isolates are farmers not connected to anyone in the network. Both Thiruvananthapuram and Kollam had no isolates, which indicates that all farmers were integrated into the network, thereby enhancing inclusivity of information flow. This is significant, as isolates often face exclusion from innovation diffusion (Rogers, 2003) [23].
- Average degree, or the average number of connections per farmer, was 4.90 in Thiruvananthapuram and 4.83 in Kollam. These values suggest a moderate level of interaction, comparable to earlier findings on farmer networks where moderate degree facilitated peer learning but required reinforcement for rapid adoption (Beaman *et al*., 2018) [5].
- Degree centrality reflects the importance of a farmer in receiving or sending information. The maximum degree centrality was 19 in Thiruvananthapuram and 20 in Kollam, suggesting that key farmers acted as hubs in both districts. The minimum degree centrality was 1 in both districts, showing that some actors remained at the margins with fewer connections. Central hubs often act as opinion leaders and accelerators of innovation (Ashraf *et al*., 2009; Borgatti, 2005) [3, 6].
- Closeness centrality measures how easily an actor can access information from others. The highest closeness was 0.682 in Thiruvananthapuram and 0.778 in Kollam, indicating that certain farmers in Kollam were better positioned for rapid access. Conversely, the lowest closeness values (0.326 and 0.333) highlight poor integration of some members, a challenge noted in farmer ICT adoption studies (Soylu *et al*., 2016) [28].
- Betweenness centrality reflects the extent to which a farmer serves as a bridge between others. Kollam reported the highest betweenness value at 174.25, compared to 143.48 in Thiruvananthapuram. This indicates that bridging roles were more pronounced in Kollam, consistent with the argument that bridging actors enhance information flow across subgroups (Granovetter, 1973; Rogers, 2003) [13, 23]. The minimum betweenness centrality was 0 in both districts, meaning some farmers did not act as intermediaries, a common feature in heterogeneous networks (Munshi, 2004) [18].

Table 2: A comparative table of node properties of the Social Network Analysis

Sl. No	Thiruvananthapuram						Kollam					
	Actor	Degree	Actor	Betweenness	Actor	Eigen Value	Actor	Degree	Actor	Betweenness	Actor	Eigen Value
1	LF	3	FF18	0.173	AO	0.149	AO	2	FF5	1.456	FF11	0.175
2	FM	3	LF	0	KAU	0.05	FF8	2	FF8	0.42	FM	0.173
3	KAU	2	FM	0	ID	0.044	FF11	2	FF13	0.42	COOP	0.143
4	FF18	1	ID	0	LF	0.043	FF13	2	AO	0.327	AO	0.108
5	ID	0	KAU	0	FM	0.043	LF	1	LF	0	LF	0.043

The SNA revealed distinct information network structures in Thiruvananthapuram and Kollam. In Thiruvananthapuram, Local Farmers (LF) and Friends (FM) held the highest degree values, signifying their importance as immediate information providers. Kerala Agricultural University (KAU) was also connected but less dominant. Similar reliance on peer groups has been noted in other studies where social proximity enhanced advice sharing (Aishwarya *et al*., 2023) [1].

Betweenness scores identified FF18 as the sole bridging actor in Thiruvananthapuram (0.173), indicating dependency on a single broker. In Kollam, however, multiple Farmer Friends (FF5, FF8, FF13) along with the Agricultural Officer (AO) performed brokerage roles, creating a more balanced network. This distribution reduces risks and aligns with findings on farmer representatives as key communicators (Yamini *et al*., 2024) [36].

Eigenvector analysis revealed that institutional actors were influential in Thiruvananthapuram, with AO (0.149) and KAU (0.050) at the core. In Kollam, peer actors such as FF11 (0.175) and FM (0.173) dominated, while cooperatives and AO also played important roles. This shows stronger synergy between formal and informal actors in Kollam. Comparable dynamics have been reported where institutions and peer groups jointly shaped knowledge flows (Aishwarya *et al*., 2023) [1].

Overall, informal actors dominated in accessibility, while institutional actors shaped structural stability. Thiruvananthapuram networks were larger but fragile due to reliance on a single broker, whereas Kollam networks were denser and more institutionally anchored. Strengthening ties between AO, KAU, cooperatives, and informal brokers (LF, FM, Farmer Friends) is necessary for inclusiveness. The existence of peripheral actors highlights the need for targeted extension strategies to ensure no farmer remains excluded, echoing findings that cooperatives enhance cohesion (Govindan *et al*., 2024) [12].

Conclusion

The study revealed that neighbours and local farmers were the most accessible information sources for JLG women farmers, while institutional actors as Agricultural Officers, Kerala Agricultural University, and cooperatives ensured credibility and structural stability. The networks were larger but fragile due to dependence on a few brokers in Thiruvananthapuram, whereas Kollam, networks were denser and more institutionally integrated. The results highlight the importance of strengthening linkages between formal and informal actors to enhance inclusiveness and resilience in information sharing. Extension strategies should focus on empowering Farmer Friends, improving institutional outreach, and integrating peripheral actors into the mainstream flow to ensure equitable and effective knowledge dissemination.

References

1. Aishwarya J, Ramu P, Rajan S, Thole S. Data-driven analysis of social capital in Farmer Producer Companies. Heliyon. 2023;9(12):e17489.
2. Aker JC. Dial A for agriculture: A review of information and communication technologies for agricultural extension in developing countries. Agric Econ. 2011;42(6):631-647.
3. Ashraf N, Giné X, Karlan D. Finding missing markets (and a disturbing epilogue): Evidence from an export crop adoption and marketing intervention in Kenya. Am J Agric Econ. 2009;91(4):973-990.
4. Bandiera O, Rasul I. Social networks and technology adoption in Northern Mozambique. Econ J. 2006;116(514):869-902.
5. Beaman L, BenYishay A, Magruder J, Mobarak AM. Can network theory-based targeting increase technology adoption? World Dev. 2018;112:236-253.
6. Borgatti SP. Centrality and network flow. Soc Netw. 2005;27(1):55-71.
7. Borgatti SP, Everett MG, Johnson JC. Analyzing social networks. London, UK: SAGE Publications; 2018. 296 p.
8. Doss CR. Women and agricultural productivity: Reframing the issues. Dev Policy Rev. 2018;36(1):35-50.
9. FAO. Information and Communication Technology (ICT) in Agriculture: A Report to the G20 Agricultural Deputies. Rome, Italy: Food and Agriculture Organization of the United Nations; 2017.
10. Freeman LC. Centrality in social networks: Conceptual clarification. Soc Netw. 1979;1(3):215-239.
11. Gladwin CH, Thomson AM, Peterson JS, Anderson AS. Addressing food security in Africa via multiple livelihood strategies of women farmers. Food Policy. 2001;26(2):177-207.
12. Govindan K, Prabhakar CS, Suresh P. Unveiling constraints in banana value chains: Evidence from Palakkad district of Kerala. Indian J Ext Edu. 2024;60(4):85-91.
13. Granovetter MS. The strength of weak ties. Am J Sociol. 1973;78(6):1360-1380.
14. Jagriti R, Nirmala G, Beevi A, Shankar KR, Nagasree K, Pankaj PK, *et al*. Structural analysis of social network among farmers for information acquisition in rainfed areas. Indian J Ext Edu. 2021;57(1):1-6.
15. Joseph J, Nirmala G, Beevi A. Identifying opinion leaders in farmer communities: An application of social network analysis. Indian J Ext Edu. 2016;52(2):32-36.
16. Kumar RM, Nagesha YN, Ranganath G, Boraiah B. Digital literacy in Indian farming: Opportunities, challenges and lessons. Mysore J Agric Sci. 2022;56(3):16-28.
17. Meena MS, Singh KM, Meena RS. Constraints perceived by farmers in transfer of technology under KVK system. Indian J Ext Edu. 2012;48(3&4):94-97.
18. Munshi K. Social learning in a heterogeneous population: Technology diffusion in the Indian Green Revolution. J Dev Econ. 2004;73(1):185-213.
19. Negi DS, Birthal PS, Roy D, Khan MT. Farmers' choice of market channels and producer prices in India: Role of transport and communication. Food Policy. 2018;81:106-121.
20. Pingali P. Green Revolution: Impacts, limits, and the path ahead. Proc Natl Acad Sci USA. 2012;109(31):12302-12308.
21. Reserve Bank of India. Priority Sector Lending - Targets and Classification. Revised Master Circular. Mumbai: Reserve Bank of India; 2015. p. 112.

22. Riaz S, Shah BH, Iqbal MK. Information-seeking behaviour of farmers in Punjab. J Agric Res. 2022;60(2):173-177.
23. Rogers EM. Diffusion of Innovations. 5th ed. New York, USA: Free Press; 2003. p. 551.
24. Sebastian AJ, Jeyalakshmi G. Use of digital tools for horizontal spread of agricultural technologies by farmers of Kerala. J Ext Edu. 2019;31(4):6442-6448.
25. Singh AK, Meena MS, Bharati RC, Kumar S. Application of social network analysis in agricultural extension research: Methodological issues and empirical evidence. Indian J Ext Edu. 2019;55(4):1-7.
26. Singh S. Strengthening agricultural extension in India: Gaps and strategies. Indian J Ext Edu. 2019;55(3):10-15.
27. Singh R, Singh KM, Meena MS. Social network analysis for strengthening agricultural extension research: Emerging perspectives. Indian J Ext Edu. 2020;56(4):12-18.
28. Soylu D, Aydin S, Yildirim Y. Farmers' adoption of ICT for agricultural extension: The case of Erzurum Province, Turkey. Inf Technol Agric. 2016;2(1):20-29.
29. Spielman DJ, Davis K, Negash M, Ayele G. Rural innovation systems and networks: Findings from a study of Ethiopian smallholders. Agric Human Values. 2011;28(2):195-212.
30. Tendulkar R, Soman S. Information flow and network structures among Indian farmers: Insights from social network analysis. J Rural Dev. 2021;40(3):455-470.
31. Valente TW. Social networks and health: Models, methods, and applications. New York, USA: Oxford University Press; 2010. p. 277.
32. Vishnu P, Venkataram M, Singh R. Social networks and the uptake of livestock technology: Evidence from rural India. Indian J Anim Sci. 2019;89(2):45-52.
33. Wasserman S, Faust K. Social network analysis: Methods and applications. Cambridge, UK: Cambridge University Press; 1994. p. 825.
34. Wood BA, Blair HT, Gray DI, Kemp PD, Kenyon PR, Morris ST, *et al*. Agricultural science in the wild: A social network analysis of farmer knowledge exchange. PLoS One. 2014;9(8):e105203.
35. World Bank. World Development Report 2021: Data for Better Lives. Washington, D.C., USA: The World Bank; 2021. p. 350.
36. Yamini P, Reddy VC, Rao DP. Unearthing agricultural influencers: Leveraging social network analysis to identify key communicators in the farming community. Ind Res J Ext Edu. 2024;24(2):112-118.